Behavioral Biases in Housing Markets

- *The Case of Oslo*

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Abstract

This thesis highlights findings from behavioral economics in the context of real estate markets, and the housing market in particular. Behavioral biases such as loss aversion, anchoring, herding, investor sentiment, charm pricing and round numbers bias are addressed.

In the empirical part, the Oslo housing market for freeholder dwellings in the period of 2006 to 2013 is analyzed. The value evaluations of professional surveyors are found to be good estimates of a dwelling's market worth, however they are lower than final sales prices on average, and might not sufficiently incorporate all available information.

I find widespread clustering of all price measures in the data; value evaluations and final sales prices cluster at round numbers, asking prices cluster at charm prices. The role of round numbers as focal points is considered, and estimated coefficients show that a million kroner focal point attracts 44% more sales than other 50 000kr price points. The relative effects of different focal points appear to be stable across time. However, the pull of mass is stronger from above the focal point than below, which might be interpreted as a pull from the seller's side of the distribution.

Finally, different designs of asking prices are considered. The data reveals that round number pricing, and setting the asking price equal to value evaluation are the most favorable designs in terms of final sales price. Charm pricing and ”under-pricing” either has no, or a negative effect on the final sales price.

“Our comforting conviction that the world makes sense rests on a secure foundation:

Our almost unlimited ability to ignore our ignorance.”

(Daniel Kahneman, 2011b, p. 201)

Preface

"Taking everything into consideration, one thing is impossible: rationality" - F. Nietzsche

Writing this thesis has been a long and arduous process. At times, it has been solitary and frustrating, but a select few deserve special praise for reinvigorating me and lifting my spirits. First and foremost, I would like to thank Luísa Ferreira Rasteiro Ralha for great patience and decisive advice. Thanks to my family, which always keep me in check, and provide me with aid in matters both large and small.

This thesis could not have been possible without the input of my brilliant supervisor; Ole J. Røgeberg, Senior Research Fellow at the Ragnar Frisch Centre for Economic Research. Time and again, he has provided valuable comments and insights, propelling the research further and helping me discover new aspects of the housing market.

I would like to thank the The Ragnar Frisch Centre for Economic Research for generous financial support, and for providing me with an inquisitive work environment.

The thesis has greatly benefitted from the provision of data by Professor Erling Røed Larsen and Eiendomsverdi AS.

Lastly, and most deservingly I would like to thank my fellow students at the Department of Economics for fierce discussions and good laughs.

Any remaining inadequacies are the sole responsibility of the author.

Oslo - 15.05.2015

Anders Skjærholt

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"Stated otherwise, decision makers can satisfice either by finding optimum solutions for a simplified world, or by finding satisfactory solutions for a more realistic world." - Herbert A. Simon (1979)

To an economist, the purchase of a house is often framed as a decision to buy the future flow of housing service-units the property yields. To the average household, the purchase of a house is framed as the decision to buy a home. It might seem like there is a small difference between the two perspectives outlined above. Look again. This thesis is constructed to disentangle the intricacies of behavioral biases in the housing market.

A house is not just a utility service provider. It is a place to live, make memories and experience life for better and worse. To many people, their home is their anchor in life. One could argue that this is just semantics. That comfort and security are just components of the housing utility equation. This is where I beg to differ.

There is in my opinion a fundamental difference between what our theory captures, and the processes people actually experience when they are buying/selling a house. The literature of economics is good at capturing and quantifying the pure economic incentives in markets. However, it is my conjecture that the literature has shortcomings when it comes to capturing and quantifying cognitive, emotional, and even moral sentiments that are present in markets. These sentiments have an effect on the final economic outcomes, and they can shape markets. To disregard and omit such variables in our analysis can be reasonable based on arguments of simplicity or tractability. However, the fallacy committed by us as economists is that we interpret the omission of such variables to signify their lack of importance.

When I started out writing this thesis, I set forth to quantify any possible loss aversion in the Norwegian housing market. I soon ran into identification issues, as housing prices across the country have soared almost uninterrupted ever since the housing crash of 1988. Therefore, I had to reconsider my approach and adjust my research inquiry to the current market conditions.

Which behavioral biases persevere in a booming housing market?

The purpose of the first few chapters is to give an overview of some key features of behavioral economics. In particular, I will address how these insights are applied to real estate markets. The many and non-unified approaches that sets behavioral economics apart from more orthodox strands of economics is a double-edged sword. In many ways, it allows researchers to revisit and rediscover traditional topics with fresh scrutiny. It also allows for investigation of different and new research areas altogether. However, this comes at a cost of a less cohesive theoretical framework, which makes dispersed contributions harder to assess in a unified way. In search of a "common denominator" to interpret the literature by, we will make use of prospect theory as our starting point.

The structure of the thesis is as follows:

A short primer of prospect theory is offered in section 1.1, and will act as our theoretical reference point throughout the thesis. In turn, I review key research contributions on the topics of loss aversion, anchoring, focal points and round numbers, as well as charm pricing. Section 1.4 provide insights on the nature of expectations, both rational and non-rational.

Section 2 introduces the dataset used in the empirical analysis of this thesis, and provides some summary statistics of typical attributes of the Oslo housing market.

Section 3 is the empirical part of this thesis and is designed to analyze the interrelations of value evaluations, asking prices, and final sales prices. Section 3.1 dissects how surveyors set their value evaluations. Section 3.2 raises the question of which listing price design has the most favorable effect on final sales price, charm pricing or round number pricing? Section 3.3 looks at how sales prices cluster at round numbers, and how focal points attract excess mass of sales.

Finally, section 4 concludes and summarizes the contributions of this thesis.

The key learning outcome will be to construct an understanding of how behavioral influences might affect both market participants, and market outcomes in the Oslo market for housing.

1.1 Prospect Theory

Prospect theory (PT) is perhaps the most common departure from one of the central tenets of economics, the expected utility theory, henceforth abbreviated EUT (Von Neumann & Morgenstern, 1944). PT, as developed by Kahneman and Tversky (1979) will provide a useful backdrop for the main part of this thesis. The insights of the theory will help underline the importance and wider-reaching consequences that the anomalies and departures from the traditional EUT-paradigm can have on markets.

As it is neither the intention nor the main purpose of this thesis to give a comprehensive overview of the literature pertaining to both expected utility theory and non-expected utility theory I would advise the reader to reference *"Prospect theory: For risk and ambiguity"* (Wakker, 2010) for valuable insights. However, to get us off on an equal footing I shall start with an overview of Prospect Theory.

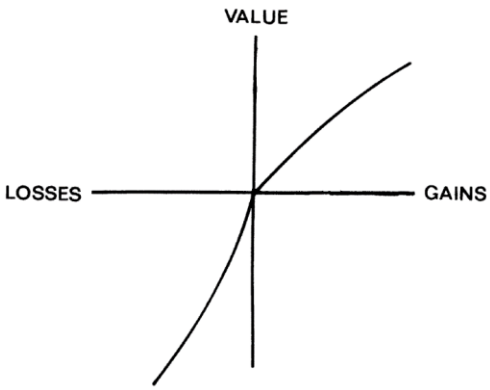

Figure 1 - (Daniel Kahneman & Tversky, 1979) - A Hypothetical Value Function

The Figure 1 shows the graphic representation of a so-called value-function, which is central to Prospect Theory. The distinct S-like shape implies that the value function is convex over the domain of losses, and concave over the domains of gains. Hence, the theory suggests that people may act risk-seeking when facing losses, and risk-averse when facing gains. The breakpoint centered at the origin is due to the incorporation of a reference point in Prospect Theory. As opposed to EUT, which assumes that final states of wealth are the key carriers of utility, PT ascribes losses and gains relative to a reference point to be the carriers of utility. The breakpoint is incorporated in PT to account for the common findings in experimental economics that "...losses loom larger than gains" (Kahneman and Tversky 1979, p. 279).

This discontinuity implies that agents suffer from loss aversion and that inertia is frequently assessed as a favorable option. A larger gain is needed to outweigh the disutility of a set amount of loss; therefore, the theory predicts that agents will be reluctant to realize losses. If the option is between action A, which is uncertain to bring either a loss or an equivalent gain, and action B which is to do nothing, then action B is the favored option. This favors the status-quo and contributes to inertia.

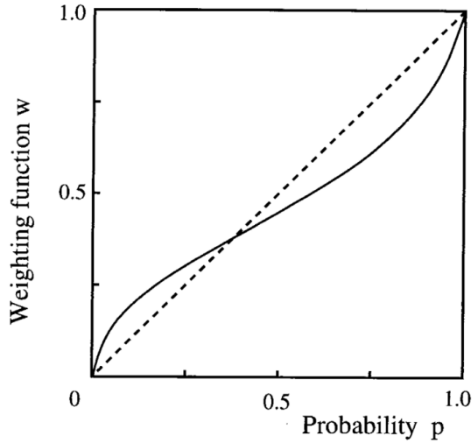

Figure 2 - (Fennema and Wakker 1997) - An Example of a Hypothetical Decision-Weight Function in Cumulative Prospect Theory

The concept of decision-weights are integral in the construction of PT. Decision-weights are allowed to be subjective and are susceptible to modification through the coding process. In EUT the decision weight is the actual stated probability, which is plotted as the 45°-degree line in Figure 2. Therefore, one can argue as Fennema and Wakker (1997) that CPT is a generalization of expected utility, as the theory allows for probabilities to be 1:1 with decision-weights, as well as allowing for decision-weights to diverge from probabilities.

In the coding and editing phase, which occurs before any decision is made, the agent interprets the available prospects with the help of heuristics. Some of these heuristics leads to consistent violations of EUT. However, since PT is a positive rather than normative theory, this is regarded as one of the strong points of the theory. Namely, to explain how and when we can expect violations of EUT, and therefore prescribe measures to guard against such biases that these heuristic decision-rules may lead to.

The coding and editing process is a personal application of a variety of heuristics and cognitive “short-cuts” of sorts that enables the agent to make complicated decisions in the matter of seconds. The process is in essence when you simplify the decision-making by rounding probabilities, discarding components shared by all the prospects, combining probabilities associated with identical outcomes, segregate riskless components, scanning for dominance and discarding extremely unlikely outcomes. This differs greatly from EUT in a number of ways.

Firstly, the process is allowed to be subjective, which is not the case in EUT. In EUT, two agents with the same information and preferences are to reach the same conclusion by calculating the highest expected value of a prospect. Through coding and editing, PT describes the many possible combinations of different heuristics that enables decision-makers to perceive prospects differently. The personal perception of a prospect can differ even when two decision-makers are facing the same information and have the same preferences. Secondly, the alteration and modification of probabilities, like rounding probabilities or discarding unlikely outcomes, is something that violates the normative calculations of EUT. The decision-rules are employed to make calculations easier and quicker, thus alleviating some of the computational constraints posed on decision-makers. These simplifications sometimes come at a great cost however, as they only give reasonable approximations most of the time. Accuracy is traded for expediency when faced by time- and computational constraints.

In this way, the coding and editing phase is what gives rise to a number of anomalies and biases that will be discussed more in-depth later in this thesis. For now, it suffices to note that coding and editing is a vital part of PT, and one of the main differences that sets it apart from EUT. Again, a caution is warranted as the process is not uniquely identified in all cases, i.e. two different people may code and edit prospects differently. This is by some seen as a weakness of the theory, that it lacks the predictive and normative power that we are accustomed to with EUT. For others it signifies a broader perspective and a less restrictive way of theorizing around processes such as decision-making. PT arguably offers something different from EUT, and emphasizes the descriptive side of actual behavior.

Another important psychological concept is included in PT, and that is the concept of diminishing sensitivity. In PT, a gain from \$110 to \$120 has less impact than a gain from \$10 to \$20, due to the diminishing sensitivity to absolute values. Parallels can be drawn to the diminishing marginal gain from standard utility-functions. In PT however, as noted previously, the value function is concave over gains and convex in the domain of losses, both expressing diminishing sensitivity as we move further away from the reference point. Furthermore, PT is distinguished by the feature of diminishing sensitivity as it also applies to the weighting function itself. That is, there is diminishing sensitivity to probability changes.

Within prospect theory, the experimental findings suggest that both particularly small and large probabilities often are susceptible to over-weighting. If we think of probabilities as having two very salient endpoints, namely 0 and 1, those values are frequently found to be invoked as reference points. This means that there is overemphasis and strong sensitivity to probabilities near the endpoints of the scale, that is 0 and 1, as this is very close to the reference point. The probabilities in the mid-range of a probability distribution are relatively insensitive to changes when applied in decision weights, as the impact of their change will be relatively small. As the mid-range values are far from either reference point, they exhibit diminishing sensitivity within the context of prospect theory. This yields the characteristic inverse S-shape of the Cumulative Prospect Theory (CPT) weighting function, as shown before in Figure 2. Note that CPT has some departures from PT, but to us the most notable difference is that PT violates the principle of stochastic dominance and CPT does not, due to the way decision weights are constructed.

Lastly, there is a need for some words of caution. PT was developed to account for a series of experiments and findings that showed patterns of inconsistencies with EUT. As experiments are mostly conducted in highly stylized settings and controlled environments, that is the very context in which prospect theory is most suitable. Particularly, all experiments had clearly defined options and explicitly stated probabilities. Those requirements are often not met in the real world.

Ever since its inception, prospect theory has inspired an ever-expanding field of research. This has led to the application and use of prospect theory in settings that are far-removed from the foundations on which it was built. For instance in a market context, it is difficult to map all possible options and choices, and even more difficult to clearly define the probabilities that are ascribed to each choice. What constitutes a reference point is also a key question. Is it the status quo, or the expected outcome or something entirely else? Another point to be made is that prospect theory describes *individual* choice. There are, as to my knowledge, no definitive guidelines as to how to apply it in the aggregate. The most common approach seems to sidestep this problem and assume linear aggregation, thus assuming every individual makes the same decision. As previously described, the coding and editing process is innately subjective and can differ between people. Therefore this issue still remains unresolved in a satisfactory manner. These are examples of methodological concerns that need careful attention, and as we proceed, an effort is made to highlight these issues. Naturally, when inserting prospect theory into a completely new setting, and applying it as theoretical foundation for explanatory factors in observed outcomes, caution and comment is warranted.

Daniel Levy (1992) is an apt example on how to apply Prospect Theory in a new context. His research shows the promise of prospect theory within other fields than economics, by applying it to international relations. Careful consideration is applied to the methodological difficulties that arise from this exercise, and he argues that empirical evidence that is congruent with the predictions of prospect theory is not enough to validate its use. Levy argues that there is a necessity to compare findings to a rational choice model, and that prospect theory needs to validate itself as a comparatively better fit to empirical data. That exercise is a stringent, but not unambiguous requirement.

N. C. Barberis (2013, p. 179) highlights a more pluralistic stance in his review that commemorates 30 years of prospect theory in economics. It is <u>*not*</u> a question whether we should <u>*replace*</u> traditional models with prospect theory, but how we can gain from implementing both types of models, that should be of interest to our discipline.

1.2 Loss aversion

As underlined in chapter 1, loss aversion is essentially the observed behavior that people require a disproportionate large gain to offset a loss. In contrast to expected utility theory this implies that if you initially have $200, and then lose $100, only to recuperate the $100 dollars again later, then you are not back to where you started. This is contingent on the reference point shifting from $200 to $100 in the process. The loss of $100 weighs more heavily on you than the equivalent sized gain of $100. To build intuition we might consider it analogous (but in no way identical) to loosing 50% of your wealth, only to immediately be followed by a 50% gain. If your initial wealth was $200, then after losing and re-gaining 50%, you now only hold $150 in wealth. When carriers of utility are gains and losses, then reference-dependence and loss aversion are likely to impact decision-making.

"*Reference-dependence and loss aversion help account for several phenomena of choice. The familiar observation that out-of-pocket losses are valued much more than opportunity costs is readily explained, if these outcomes are evaluated on different limbs of the value function.* (D. Kahneman, 2003, p. 1457)

The quote above illustrates yet again the departure from standard economic reasoning that all economic factors are to be valued according to their alternative best use, e.g. the opportunity cost. It is the kink of the prospect theory value function at the reference point, which accounts for the over-weighting of losses compared to gains. If an opportunity cost is, as Kahneman suggests, perceived as a foregone gain, and an out-of-pocket loss is evaluated as a true loss, then according to prospect theory we would pay less attention to the opportunity cost, and strongly focus on out-of-pocket losses. This does not fit in with standard economic assumptions, but it is often recognized in law, where reparations and compensation makes a clear distinction between actual incurred losses and opportunity costs (Cohen & Knetsch, 1992).

In general, there has been extensive research on loss aversion across a various field of markets, experimental settings and in different disciplines, spanning more than 30 years of research. Behavior that is consistent with loss aversion has been discovered in everything from trading of college basketball tickets to orange juice purchases and its occurrence seems ubiquitous, see Novemsky and Kahneman (2005) for a brief historical overview. Kahneman and Tversky are the central contributors to the field and responsible for introducing and coining the term loss aversion (See their defining papers; (1979);(1991);(1992)). In 2002, the psychologist Daniel Kahneman, together with experimental economist Vernon L. Smith, received the memorial Nobel Prize in economic sciences. As motivation for the award, the committee emphasized Kahneman's contribution through his work on integrating psychological factors in the domain of economic activities. This was partly in recognition of the importance, and the growing influence of concepts such as loss aversion and anchoring.

Together with Richard Thaler and Jack Knetch , D. Kahneman (1991) made use of experiments to analyse the empirical grounds of loss aversion as a regular occurrence in economic activities. Shlomo Benartzi and Richard Thaler (1993) used loss aversion to offer an explanation of Mehra and Prescott's (1985) equity premium puzzle, the idea being that loss-averse investors forego long-run gains because of a combination of their myopia and loss aversion. In a more recent paper Banerji and Gupta (2014) use a novel auction design to elicit and identify the magnitude of loss aversion in auctions. They offer a design that can mitigate bias in the standard Becker-DeGroot-Marschak mechanism that arises when dealing with loss-averse participants. In addition, the increasing focus on the burgeoning field of neuro-economics has led to an appreciation of the cognitive side of economic theory. In an effort to build a nexus between insights from behavioral economics and neurological science, it was shown that loss aversion can be attributed to activity increases and decreases, in particular brain-regions (Tom, Fox, Trepel, & Poldrack, 2007).

These are all examples of the variety and plethora of research on loss aversion. In the following, I will emphasize loss aversion in the real-estate markets, and the effects it can have on the aggregate outcome. A sub-categorization of loss aversion is found in Appendix A to gain a better understanding of the concept as a whole. There I evaluate money illusion as well as the disposition effect and the endowment effect, whilst showing their connections to loss aversion.

1.2.1 Loss aversion in Real Estate Markets

A number of researchers report evidence of loss aversion (Anenberg, 2011; Bokhari & Geltner, 2011; Einiö, Kaustia, & Puttonen, 2008; Engelhardt, 2003; Genesove & Mayer, 2001; Stephens & Tyran, 2012). The combination of prospect theory and real estate markets was brought forward by Genesove and Mayer's paper (2001), where they estimated the impact of loss aversion in the Boston condominium market. They found a significant effect of nominal loss aversion, while controlling for liquidity constraints. The sellers, who were facing a nominal loss in the market, set a higher asking price than sellers not subjected to a prospective loss. This would suggests that path-dependency matters (David, 2007), and that sunk-costs are treated as a normal cost.

While the excess asking prices may be caused by behavioral influences, the trade-off the sellers make is to face a longer time on the market, which can be fully explained by rational choice theory. However, the loss-averse sellers also receive part of that excess asking-price when selling, indicating that the market actually responds to their bias. In the words of the authors: *"Thus the high asking-prices set by those with a potential loss are not simply brief and irrational "wish" statements that the market quickly corrects"* (Genesove & Mayer, 2001, p. 1236).

I will elaborate on this point in the section 1.6 regarding markets, experience and how to mitigate behavioral biases. For now we note that loss aversion can occur in functional markets, and move on to take a closer look on the distinction between liquidity effects and loss aversion in the housing market.

Genesove and Mayer's analysis was offered as an explanation of the positive correlation between price and volume observed in most real estate markets (Jim Clayton, Miller, & Peng, 2010). Ever since Stein (1995) proposed his housing model with down-payment constraints, there has been competing explanations for the positive price-volume correlation found in the data. The question has been whether the analyses are measuring the down payment/liquidity-constraint or a factor of loss aversion. As G&M's 2001-paper is a follow up to their work on liquidity constraints in 1997 (Genesove & Mayer, 1997), the latest paper explicitly addresses this issue, and concludes that their previous estimates of liquidity-constraints effect on prices are halved when including loss aversion in the regression (Genesove & Mayer, 2001).

However, a word of caution is warranted here, as their latter paper uses an extended dataset the regression-coefficients are not directly comparable. Even so, Genesove and Mayer conclude that their first analysis greatly overestimated the impact of liquidity constraints due to omitted variable bias.

Chan (2001), Engelhardt (2003) and Anenberg (2011) find similar evidence of loss aversion in a variety of real-estate markets across the U.S. In summary, it is a strong indication of loss aversion in housing markets that is robust across dimensions of time and space. The effect in the marketplace stemming from loss aversion varies across the literature. Engelhardt (2003) finds that a 5% nominal loss is associated with a 30-44% reduction in the probability to move. In Einiö et al. (2008) they find that losses are much less frequently realized than gains in the Helsinki housing market, while controlling for the relative possibility of incurring a loss or gain. Lastly, in the most recent paper (Bokhari & Geltner, 2011) they find that sellers facing a loss, relative to their prior purchase price, set an asking price which is higher than those not facing a loss by a magnitude of 38% of their loss exposure. This leads to a final sales price, which is higher than if they were not facing a loss by the magnitude of 24.5% of their loss exposure. These findings are of approximately the same magnitude as Genesove and Mayer's (2001) estimates; Asking prices were found to be higher for sellers facing a loss, at a magnitude of 25% to 35% of the loss exposure, and the final sales price was also higher than if the seller was not facing a loss, measured to 3-18% of the loss exposure. To put it plainly: a seller facing a $100 000 loss is likely to set an asking price which is from $25 000 to $38 000 higher, and receive a sales price which is between $3 000 to $24 500 higher than if he was not facing a loss.

1.3 The Behavioral Influence of Prices

In undergraduate economics we are taught that prices are signals, which incorporate a lot of information in a very efficient and expedient way. In fact, this is often celebrated as one of the great achievements of markets. The call for legalization of prediction markets, which can process uncertain information in a systematic way, made by a series of Nobel laureates and prominent scholars can stand as an example of that (Arrow et al., 2007). However, the perception, interpretation and processing of prices may vary between different populations, and even change across time within subjects. This is a less commonly emphasized feature of prices, which has gained much more attention within the field of behavioral economics. This section tries to assess a few key points that might affect the price setting and strategies in the housing markets.

Mental accounting, as defined by Richard H. Thaler *(1999, p. 183)* is: *".. the set of cognitive operations used by individuals and households to organize, evaluate, and keep track of financial activities."*.

It perhaps sounds like something that is unconditionally a good thing. However, this special type of "mental arithmetic" tends to violate the assumption that final states of wealth are the carriers of utility, and leads to a breakdown in the fungibility of funds. Non-fungibility means that money allotted to one specific purchase is no longer a perfect substitute for another purchase. An oft mentioned example of this is the concept of "house money" found amongst gamblers. The money that is won at the casino are treated different, perhaps spent in a more cavalier way than the money they brought into the casino.

Seiler, Seiler, and Lane (2012) find strong indications of mental accounting in their survey experiment pertaining to real estate markets. This, they find, is coupled with false-reference points, which concurrently affect the decision-maker. Most of the participants in their study make use of the break-even point as a false reference point. It is false in the sense that a rational decision-maker knows that the past purchase price is a sunk cost, and thus it should not matter for the decision to hold or sell.

Thaler himself intimately links the development of the mental accounting theory to that of prospect theory (R. H. Thaler, 1999). In the widest sense of the words, mental accounting encompasses all of the coding and editing process found in prospect theory, as well as related concepts such as framing and the evaluation of events. Mental accounting adopts the value function found in prospect theory and thus includes the features of a reference point and loss aversion.

An instructive example of mental accounting comes from A. Tversky and Kahneman (1981) where it is found that people tend to be willing to incur a given transaction cost when the prospective saving is large in terms of percentage of the good, however they are not willing to incur the cost when the prospective saving is low, measured in percentage of the good in question.

"Imagine that you are about to purchase a jacket for ($125)[$15] and a calculator for ($15)[$125]. The calculator salesman informs you that the calculator you wish to buy is on sale for ($10)[$120] at the other branch of the store, located 20 minutes drive away. Would you make the trip to the other store?" (Tversky and Kahneman, 1981, p. 459)

It is found that most people would like to save five dollars on the calculator, but not the jacket.

1.3.1 Anchoring

"Highly accessible values are generally overweighted, and when considered as possible answers to a question they become potent anchors" – Daniel Kahneman (2002, p.482)

Ever since Northcraft and Neale (1987) there has been considerable interest in anchoring and adjustment processes in real estate in particular. They devised a quite intuitive and appealing study in which both students and professional realtors were presented a property to assess. The subjects were all taken on-site to actually see the house in question and received an information package akin to the usual information supplied by a real estate agent. The treatment variable they provided was an asking price, which they varied throughout the study. This asking price turned out to be a salient anchor, which influenced both the professionals' and students' estimate of the market worth.

The asking price varied from +-4% to +-12% above and below the actual assessed price, as given by a professional surveyor. Anchors of this kind are likely to have an impact on inexperienced participants (students), but should (in theory) not affect the professionals when determining the value of the house. Northcraft & Neale interpret their findings as compelling evidence that realtors indeed were affected by the given listing price. The realtors' predictions were biased upwards when given a high initial estimate. Correspondingly, their assessments were biased downwards when given a low initial estimate.

In the ensuing questionnaire survey of the participants, both students and professionals reported that they made use of comparison computations involving neighborhood characteristics and past transactions, as well as the listing price. However, the experts were much less likely to report the listing price as one of their three most decisive factors. It seems as both groups were unaware that the potent anchor might bias their estimates, and that this contributes to the insufficient adjustment away from it.

As Northcraft and Neale (1987, p.95) concludes*: "It remains an open question whether experts' denial of the use of listing price as a consideration in valuing property reflects a lack of awareness of their use of listing price as a consideration, or simply an unwillingness to acknowledge publicly their dependence on an admittedly inappropriate piece of information."*

At the very least, this finding should advise us to allow for the possibility that anchors might affect the decision making process in the housing market.

1.3.2 Focal-Points / Round Numbers

"The effects of salience and anchoring play a central role in treatments of judgment and choice. Indeed, anchoring effects are among the most robust phenomena of judgment, and overweighting of salient values is likely to be the mechanism that explains why low-probability events sometimes loom large in decision making" - Daniel Kahneman (2002, p. 482)

Although related to anchoring, focal points and round numbers are more specific in the way that they only relate to a few select values in the housing price distribution. Specifically, an integer followed by a string of 0's is conceptualized to constitute a round number, e.g. $50 000 or $300 000, etc. This particular design of price might evoke special cognitive processes within the buyer.

The concept of focal points in bargaining processes is attributed to Thomas Schelling by Pope, Pope, and Sydnor (2014), which allows for a more diverse bargaining process than what is found within the standard axiomatic approach put forward by Nash. The Nash approach requires symmetry; essentially that both parties have rational expectations and follow the same rules of behavior. In Schelling's framework focal points may represent common thresholds that help bargainers meet at certain levels. In this way, focal points can help avoid bargaining impasse, and speed up the bargaining process as the increments of the bargaining offers are large. As the empirical analysis in section 3.3 closely follows the approach of Pope, Pope and Sydnor, I will interpret the round numbers pricing as focal points, and the two terms are used interchangeably.

Let us now focus on some reports of round numbers in the literature. In a worldwide review of consumer surveys from 38 countries Curtin (2007) examines more than 52.000 cases of probability-questions from University of Michigan's consumer sentiment surveys in the period 1998-2006. He finds that there is a strong occurrence of incomplete use of the whole range of the probability scale, by the respondents. That is, respondents only tend to use a few salient numbers in their answers to questions regarding probability, and not the whole range of the scale.

For instance, when asked: “Personal income will increase during next twelve months”, respondents reported full certainty (either “0%” as answer or “100%” as answer) in 32% of the cases. Quarter rounding, that is a response of either 25%, 50% or 75%, was the answer of 20% of the subjects. The use of “ten-rounding numbers”, that is 10, 20, 30, 40, 60, 70, 80, 90, were replied by 38% of the subjects.

“Why did the vast majority of respondents choose so few points out of the range from 0 to 100? The most common answer is that the responses represent "rounded" estimates.” (Curtin, 2007, p. 24)

Together, those salient numbers constitute only 13/100 of the possible range of a probability distribution. In the aggregate, those 13 values account for 90% of the cumulative probability reported by the 26101 cases in the sample from 2002-2006. This can be interpreted as a round numbers bias and a reliance of salient numbers.

In the literature, it is not given that this kind of rounding is the effect of a behavioral bias. It might be that the coarseness of the estimates that are provided, represent the trade-off between cognitive strain and response-time. This has been proposed as an explanation, namely that people round off their estimates and responses, as a matter of convenience. This is what I will refer to as the convenience-rounding heuristic. However, the potential scope of such an explanation is limited, as it should not affect high stakes decision-making, where outcomes are greatly affected by this kind of rounding. It is my contention that the housing market is exactly this type of high-stakes environment. A plausible framework for interpretation of this type of behavior is that of Herbert A. Simons “bounded rationality” (1955). In Simon’s theory, agents are satisficers who balance the computational costs of a given problem with the limited cognitive resources of the human mind. Thus, the notion is that people simplify and round of estimates, as it reduced computational demands.

Palmon, Smith, and Sopranzetti (2004) find that dwellings where the asking price is on a round number, sell both faster and for higher sales prices as compared to those that were listed with an asking price at a just-below round number (commonly interpreted as a charm price). However, as discussed in the subsequent section, the empirical results found in the literature are conflicting when it comes to which pricing strategy results in the highest final sales price; round numbers or charm pricing. Palmon, Smith and Sopranzetti focus on the precision of the asking price, and other papers have shown that a more precise asking price may signal that the seller has superior knowledge of his dwelling’s worth, and that it leads to better bargaining outcomes (Beracha &

Seiler, 2014; Mason, Lee, Wiley, & Ames, 2013; Thomas, Simon, & Kadiyali, 2010). The section below addresses charm pricing explicitly, but round numbers- and charm pricing usually both occur simultaneously for different dwellings in housing markets. Their effects relative to one another are still debatable though, as they both claim to have a positive effect on sales price.

1.3.3 Charm Pricing / "Just-Below Pricing"

Allen and Dare (2004) analyze the design of listing prices in the market for single family houses in Fort Lauderdale, Florida over the years 2000 and 2001. They find that properties where the asking price was a charm-price (examples are prices ending in $900, $4,900 or $9,900), sold for significantly more than those who did not have a charm listing price. The analysis controlled for a number of dwelling characteristics, instrumented effects of time-on-market, and selectivity bias. As a robustness check, they found that houses that were listed with a round number asking price (e.g. ending in multiples of $10,000's or $100,000's) sold for significantly less.

In a controlled experiment approach Cardella and Seiler (2014) find that the precision of the listing price, meaning that the price is not rounded and not a charm-price (e.g. $287,455), affects the final sales price in a positive way. When looking at just below round numbers (charm-prices), they find that it yields the largest percentage difference between list price and final sale price, as well as yielding consistently low counter offers from the seller. They also argue that the different listing price strategies affect both the buyers' **and** the sellers' negotiation processes in different ways. This might indicate that the bargaining process is complex, and potentially not adequately described in conventional theory.

Bucchianeri and Minson (2013) find that anchoring was evident in three northeastern states of the U.S. over the course of 2005-2009.Relatively higher listing prices was found to lead to higher selling prices. Furthermore, underpricing/charm pricing lead to less favorable outcomes for the dwellings employing that type of listing price strategy. In a recent empirical analysis,Beracha and Seiler (2014) find that "just-below" pricing relates to shorter time on the market and higher transaction prices than precise and round number pricing in Virginia.

In rational search models it has often been assumed that the asking price is the willingness to accept. Therefore buyers are modeled as never having to paying more than the asking price, as any offer at the asking price will be accepted, see Arnold (1999) for an example of such a theoretical search model of the housing market. As chapter 2 of this thesis explicitly shows, this assumption is routinely violated as dwellings sell for more than the asking price. Thus, equating the asking price with the willingness-to-accept in the Norwegian market will yield improbable theoretical predictions.

Charm pricing can be seen in relation to the left digit bias found in psychological and marketing theory (Coulter, 2001). It has been hypothesized that the cognitive processes are biased towards only remembering the leftmost digits. Thus, charm pricing can be seen as an attempt to exploit this behavioral heuristic, however the effects of this listing price design remain an empirical issue, as the findings in the literature thus far are conflicting.

1.4 Price Expectations – Rational?

In the behavioral finance textbook by Ackert and Deaves (2010, p. 67) we find 3 requirements for market efficiency:

1) All investors are all rational
2) Investor errors are uncorrelated
3) There are no limits to arbitrage

In the housing market, and perhaps in real estate more in general, all these three foundations of market efficiency can be called into question. For instance, herding behavior (as analyzed in section 1.4) can be an example of a violation of req. 1) and 2) as investors overshoot from fundamental values and tend to follow market sentiments (Hott, 2012). There are also evident limits to arbitrage in real-estate markets, as we cannot short-sell houses, and transaction costs are large both in terms of search costs and brokerage fees. However, even if some of these three requirements are not met, Ackert and Deaves argue that market efficiency will be restored as long as at least one of the criteria holds. The most debated criteria is perhaps the assumption of perfect rationality. This section therefore looks deeper into questions about rationality, and more specifically; whether *expectations* are rational or not.

Over the course of a business-cycle the housing and real estate markets tend to fluctuate. Most of these price movements can be explained by changes in fundamentals such as, after-tax real cost of borrowing, GDP growth rates, demographic trends, construction costs and supply of new housing units. However, there is growing evidence that housing markets are not efficient, and to some extent predictable (K. E. Case & Shiller, 1990; Larsen & Weum, 2008). Expectations that violate rational assumptions has been offered as an explanation for this inefficiency in the housing market, and could potentially explain the excess returns that are observed (Jim Clayton, 1996; Shiller, 1990).

An example of the contrasting approaches to model housing markets in either rational or non-rational terms comes from Wheaton (1999). He builds a stock-flow model of the real-estate market and shows how myopic agents tend to generate cycles in the market as they make use of extrapolation of current rates to determine their investment decisions. He also shows that for the same model, now assuming rational expectations, the only way to generate cycles is for the economy to be hit by alternating exogenous shocks. The fully rational agents can predict the changes that are induced from each and every shock and adjust accordingly, but they do not know the timing of the shocks. In this way, the observed cycles in the housing market are "rationalized" such that the rational expectations assumption still holds and is compatible with observed facts.

Capozza et. al (2002) find evidence of strong auto-correlation and mean-reversion of real house prices across the board of major U.S. metropolitan areas. Their findings suggest that prices are slow to react to exogenous shocks, and prices are sticky. The authors highlight the difficulties of reconciling rational expectations with these empirical findings:

"From a theoretical perspective in which forward-looking prices should immediately incorporate all available information about future changes in real houseprices, the impact of factors affecting serial correlation is difficult to explain." (Capozza et al., 2002, p. 23).

In a rational expectations framework, expectations are to be forward-looking, however findings like Capozza et al. contradict this. Hattapoglu and Hoxha (2014) also find that households' expectations about future price appreciation is backwards-looking, but at the same time fundamental factors such as location influence them. Thus, households are perhaps best described as having a hybrid form of both rational and adaptive expectations at the same time. It is established that housing markets are inefficient, and as many before them, the authors suggest that the limited possibility of arbitrage in the housing market to some extent can be offered as an explanation.

Still, arbitrage in some sense is possible, for instance K. E. Case, Shiller, and Weiss (1993) propose a futures market for real estate and home equity insurance which would facilitate this. There is no explanation offered by Capozza et al. (2002), or in other studies of my knowledge, of why such arbitrage does not materialize quicker in the markets. If arbitrage can be made possible, and prices are predictable then "smart-money managers" should take advantage of this (Schindler, 2013). However, this seems not to be the case, and is still somewhat of a puzzle. There is in a sense, a void left to fill to make the theory add up to the empirics.

1.4.1 A Rational Framework - The User Cost Model

In the most basic sense, the user cost of capital framework treats the rental market as a perfect substitute for owner-occupied housing. The only decision to make is whether to buy or rent in this model. To consider opportunity-costs is the baseline of most rational models, and it holds true for this setting as well. Therefore, the rental price of a dwelling can be made use of as a baseline to calculate what the same dwelling is worth in the owner-occupied market. The basic relationship is that the ratio of buying-price/rental-price must equate to the inverse of the user cost of capital (Himmelberg, Mayer, & Sinai, 2005). However, the compatibility of rental dwellings as substitutes for owner-occupied housing is a debatable issue, see Borgersen and Sommervoll (2012).

The user cost of capital is a composite measure of the imputed rents from the dwelling. It is essentially an attempt to quantify what the owners would pay themselves if they had to rent their own dwelling. It is made up by foregone investment gains(opportunity cost), housing tax liabilities, mortgage rate subsidies, depreciation of housing quality, house price expectations (capital gains) and a risk premium from owning undiversifiable risk (Himmelberg et al., 2005).

Browne, Conefrey, and Kennedy (2013) look into the case of Ireland over the past three decades and employ the traditional user cost of housing framework to analyze house price dynamics. The conclusion thus far for Ireland is that the expected capital gains (house price appreciation) over large periods of time made the user cost of capital for housing <u>negative.</u> This means in principle that home-owners were not paying for their housing services, rather to the contrary; they gained from owning relative to those who rented. One can argue that part of this gain comes in the form of a subsidy from tax-payers, since housing related mortgage costs are tax-deductible (Poterba, 1984). As the authors note, it is a theoretical conundrum that a price in a functioning market can be negative, and in the Irish case it led to a vicious boom- and bust-cycle of unprecedented proportions.

"…the idea of a negative price prevailing in unconstrained private markets would seem to infringe a basic axiom of economics. It also suggests that, in equilibrium, private market rents should, according to our mode of tenure arbitrage story, also be negative which is never observed."(Browne et al., 2013, p. 15)

The authors indicate that it is the expected house price appreciation that drives most of the user cost of capital to be negative. Interest rates and taxation effects are shown to be of secondary importance when it comes to explaining the observed outcomes. The above quote aptly illustrates the problem the user cost model sometimes face when forced to explain empirically observed outcomes. When house prices are positive, and rental prices are positive, then the user cost of housing **<u>cannot</u>** be negative as it is described mathematically in the theory. However, that is what has been observed empirically.

Therefore, at least two possibilities emerge; 1) either the measures that goes into calculating the user cost of housing is wrong or 2) the mathematical relation between housing prices, rental prices and user cost of housing is wrong. Option 2 is to the observant reader, of course a euphemism for saying that the rational framework of the user cost of housing model is conceptually flawed and erroneous.

“.. if the expected capital gain is high enough, the user cost can be negative, implying that expected price appreciation outstrips the cost of capital. If that were the case, the return on home buying would be infinite and the user cost would be undefined.” (Mayer & Sinai, 2007, p. 271)

This issue is something that has been noted in the literature, but dismissed and thus never properly been addressed.

Beatty, Larsen, and Sommervoll (2010) argue that the user cost of housing confuses consumption prices with investment gains, it yields a negative user cost in times of rapidly appreciating house prices. This will theoretically imply infinite demand for owner-occupied housing, and rental prices should then also go into the negative range.

Interestingly, at the time of writing the user cost of housing in Norway will, by a reasonable set of parameter-values, yield a negative user cost. It is beyond the scope of this thesis to conduct a fully-fledged user cost analysis, but a back-of-the-envelope calculation is offered as an illustration in Appendix B.

The arithmetic show an example of the crucial role the expectations-component plays in the user-cost of housing framework. In a low interest-rate environment the expected future price dominates the equation, and gives a strong incentive to buy rather than to rent. In this sense, it can contribute to self-fulfilling prophecies in the housing market.

1.4.2 The Non-Rational Framework - Market Sentiment

To contrast the user cost model of housing, I have found it instructive to look towards behavioral finance and a theory of market sentiment. In the Barberis, Shleifer, Vishny model I will discuss, market sentiment is interpreted as the over- or under-reaction to information.

N. Barberis, Shleifer, and Vishny (1998) built a parsimonious model that can explain the empirically observed over- and underreaction in securities markets. Their motivation was to incorporate psychological factors into the market, which then could be used to explain departures from the efficient market hypothesis. Their model tries to formalize two key findings in psychological research; conservatism and the representativeness heuristic. The meaning of conservatism in the form proposed by the authors, is that people react slowly to news that are contrarian to their beliefs. People adjust their beliefs, but the magnitude of change is less than what fully rational agents would do. This concept thus has clear similarities to anchoring, which was described in subchapter 1.3.1. Conservatism is the theoretical foundation on which underreaction is based, and it is described as having a short time span of less than a year. In the real estate market, this could suggest that prices are sticky and only slowly adjust to changing fundamentals.

The representativeness heuristic stems from the research of Amos Tversky and Kahneman (1974), and in principle states that people make use of similarity and familiarity when asked to make probability assessments. How representative someone or something is of the population in question tends to outweigh proper statistical reasoning criteria such as assessing base-rates. This concept is evoked to motivate the inclusion of overreaction in the model of Barberis, Shleifer and Vishny. The intuition is that if a piece of news fits in well with the overall sentiment in the market, then representativeness kicks in and further drives the market away from fundamentals. Overreaction is based on a string of good news, and is of a longer time perspective than underreaction, about 3-5 years.

Shleifer, Vishny and Gennaioli forthcoming (Gennaioli, Shleifer, & Vishny) offer a complementary analysis to the previous model of investor sentiment. They construct a rudimentary model based on psychological theory and representativeness that can explain why risks of a crash are underweighted in boom-periods, leading to consequent crashes and financial crisis. This can be thought of as an extension of the previous model, and incorporates other behavioral features that are related to prospect theory through the under/over-weighting of probabilities which is a key feature of the coding and editing process.

Baker and Wurgler (2007) concluded already in 2007 that the debate about whether sentiment affects investments or not was over. Sentiment leads to mispricing was the answer, at least for the stock market. If we are inclined to believe that the limits to arbitrage, high transaction costs and financial nature of real estate transactions only serves to further exacerbate the effects of sentiments in the marketplace, then the debate can be put to rest at once. However, let us look at some of the indications of sentiment in real estate markets in the U.S. and in Norway.

1.4.3 Sentiment in the U.S. Real Estate Markets

Case and Shiller (1988) find using survey data, that in the U.S. in 1988 there was strong indications that home buyers exhibited backwards-looking rather than forward looking expectations. In boom markets, respondents had much higher expectations of future price increases. The authors strongly conjectured that the housing market has tendencies of booms being fueled by expectations, and that these are formed socially and not rationally or based on fundamentals. There was downward rigidity in pricing of houses amongst the respondents, and a upward volatility in prices. Lastly, they found that one of the most common influences amongst buyers was investment motives.

In a follow-up study conducted in 2012, over a long sample of surveys spanning 2003-2012, the authors found that home buyers were rational, and actually underreacting, in their short-term (1 year) expectations of the housing market. However, the 10 year expectations seemed to be backwards-looking and overreacting, which was a point the authors argued for, but could not verify at the time (K. E. Case, Shiller, & Thompson, 2012). Now that we can compare in hindsight, it looks as if they were correct.

For example, in Boston in 2003 they expected an 8,9% increase on average per year for each and every year until 2013. The actual price development was only a meagre 0,47% increase on average per year, calculated using S&P/Case-Shiller MA-Boston Home Price Index© from the FRED database (Federal Reserve Bank of St. Louis, 2015). This yields an overestimation of 8,43% per year.

That is, respondents expected the house prices to increase 8,43% each and every year for 10 years <u>in excess</u> of the *actual observed* price development. Similar results can be shown for the other metropolitan areas included in the Case, Shiller and Thompson (2012) study. The numbers are perhaps largely a reflection of the fact that prices were increasing rapidly in the period 2003-2005, but had a huge downturn, and only now as of 2015 are returning to something resembling the magnitude of pre-crisis peak levels. If expectations are backwards looking and market sentiment shapes the expectations about future price growth, then we would expect to find that people overestimate future growth rates, when those expectations are measured during the upswing of a housing price cycle. We can note that this is consistent with the figures described above.

The findings of Case, Shiller and Thompson can be interpreted in the light of the investor sentiment model of Barberis, Shelifer and Vishny. The finding that buyers are underreacting to news in a 1 year perspective can be explained by conservatism. The extremely high estimates of 10 year growth rates can be interpreted as overreaction or as an effect of the representativeness heuristic that follows from a string of good news (increasing prices).

In the commercial real estate markets in the U.S., which is populated by professionals, J. Clayton, Ling, and Naranjo (2009) put the concept of investor sentiment to a test over a ten-year period. They find that fundamentals explains most of the variation in market capitalization rates, however there is also significant evidence that sentiment played a part in the pricing of those markets. Hendershott and MacGregor (2005) give an attempt to refute prior findings of non-rational expectations, still conclude that irrationality played a crucial part in explaining market capitalization rates in the U.S commercial property market from 1984-2002. Ling, Naranjo, and Scheick (2014) again show, this time for privately traded real estate markets, that sentiment induces long periods of mispricing. They also conclude that it is the limit to arbitrage that seems to be the key factor explaining that mispricing can persist over longer periods in privately traded markets, but in public markets it is short lived and corrected in the long run.

Of the shortcomings that affect the imperfect housing markets, the lack of understanding of psychological factors may potentially be an important one.

> "*Future research could explore the micro evidence on the behavior of individual homebuyers, particularly the role of liquidity, information, and psychology.*"
>
> *(Capozza et al., 2002, p. 24)*

At the end of Appendix A, I address herding behavior, which can be seen as an outcome arising from information processing and the tendency to follow each other's actions. This is often seen as an extension or supplementary to the sentiment induced anomalies found in markets. Thus, it will give some further insights that capitalize on the theory outlined above.

1.4.4 Sentiment in Norwegian Housing Markets

Let us focus on expectations, and narrow in on the Norwegian housing market in particular.

If we for a moment hypothesize that the Barberis, Shleifer, Vishny-model is valid for real estate markets, and apply it to the Norwegian housing market, then we get an interesting case-study to analyze.

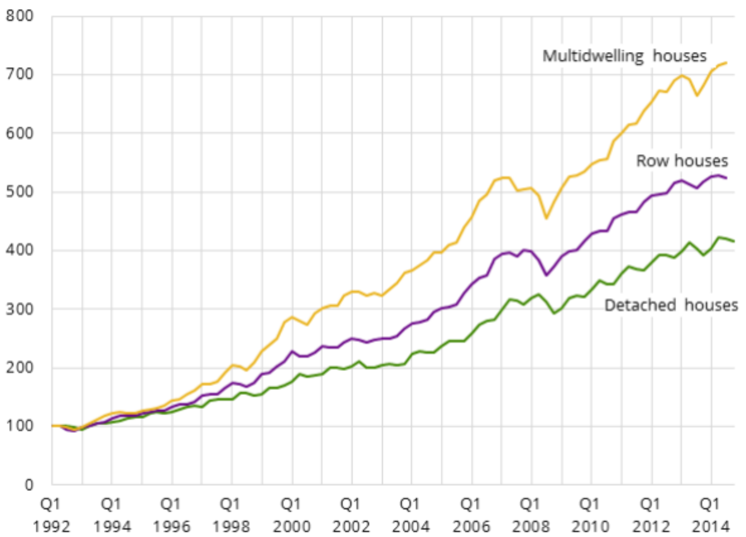

Figure 3 - (Statistics Norway, 2015b) - House Price Index, by Type of Dwelling. 1992=100

The string of good news (for house-owners) can be seen in Figure 3, which displays the house price index for Norway at a national level. The clear, and strongly upward sloping trend is only interrupted twice (for less than 6 months at a time) in the course of 22 years. When described in the ways of overreaction, Barberis, Shleifer and Vishny's model would predict that a long run of positive news will lead to large deviations from fundamental values. Expectations of future price growth are high as it is consistent and representative of the price development the past 20 years. This form of extrapolation beyond the sample would lead to large negative realized average returns if the market were to turn negative.

In consequence, there could be both an under-reaction and an over-reaction to a surprise turn of the market. If governed by conservatism then an under-reaction to the downturn in the market would ensue, and this would lead to perhaps a slower and smoother transition path downwards. However, if there is a string of bad news and people follow their representativeness heuristic, then an overreaction to the initial turn of the market will dominate.

In the comprehensive official Norwegian report about the housing market (NOU 2002:2, 2002, p. 66) it is noted that the expected future price of a house will influence the decision to buy or sell. Efficiency of the market can only be expected if people do not exhibit beliefs or misconceptions about future prices that are systematically erroneous. A vague criteria is offered to explain what is meant by systematically erroneous beliefs. It is to be considered systematic, if people are not aware that future prices cannot be predicted with any reasonable accuracy in the long run. In the report it is suggested that this will only be a part of any criteria of systematically wrong beliefs, but it can hardly be seen as a definitive measure of whether price expectations are right or wrong. The findings of K. E. Case and Shiller (1990) that housing prices are predictable, seems to conflict with the before mentioned criteria of rationality.

A more common criteria, as Case, Shiller and Thompson (2012) employ, is to regress actual observed future price onto expectations about future prices. If expectations are rational then the constant term should be zero and the slope coefficient equal to 1. This is thus a test about rationality, which predicts that the expectation of future prices should equate to actual future prices. It is in the author's view a better criteria to judge market beliefs than the "systematically erroneous" –criteria suggested in NOU 2002:2.

There are perhaps views and perceptions of how the market works in the general public that do not fit in well with the mechanisms that economists rely on. In the government report (NOU 2002:2, p. 86) it is cited indications that the Norwegian public believe that housing prices and interest rates will increase in tandem. However, in the user cost of housing model, the mechanism is that higher interest rates will, ceteris paribus, decrease house prices by increasing the user cost of housing. This should, again ceteris paribus, result in less demand, and lower prices in the market. The circumstantial evidence then suggests that the public may hold false beliefs.

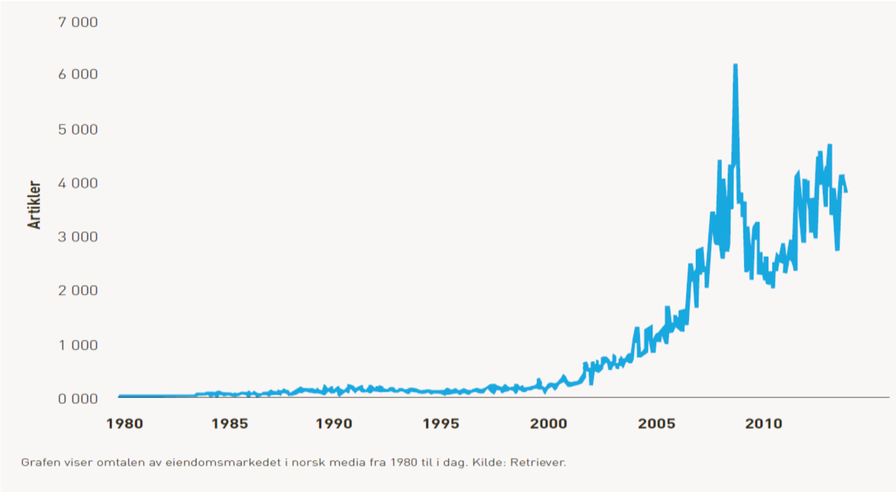

Figure 4 - (Eiendom Norge, 2014, p. 43) Number of Articles Published in Norwegian Media Relating to Real Estate 004Darkets. Source: Retriever

Case and Shiller (2012) also discuss the role of media in transmitting social sentiment and "believable stories" that affect the price expectations. In Norway we have seen media reports of late that indicate that 80% of all dwellings sold in the major cities are going for more than asking price. These are often interpreted as indicators of a hot, or booming market if you wish. This feature is highly unusual, as compared to other countries where final sales price usually is lower than the asking price (Beracha & Seiler, 2014). If expectations are backwards-looking and reinforcing, then stories like these in all likelihood contribute to further remove market prices from fundamentals. At the very least, we can conclude from Figure 4 that media attention and public interest in the housing market is quite sizable.

In Figure 5 below, I have illustrated the deviation in sales price from asking price as a ratio of the asking price, for the sample of Oslo in the years 2006-2013.

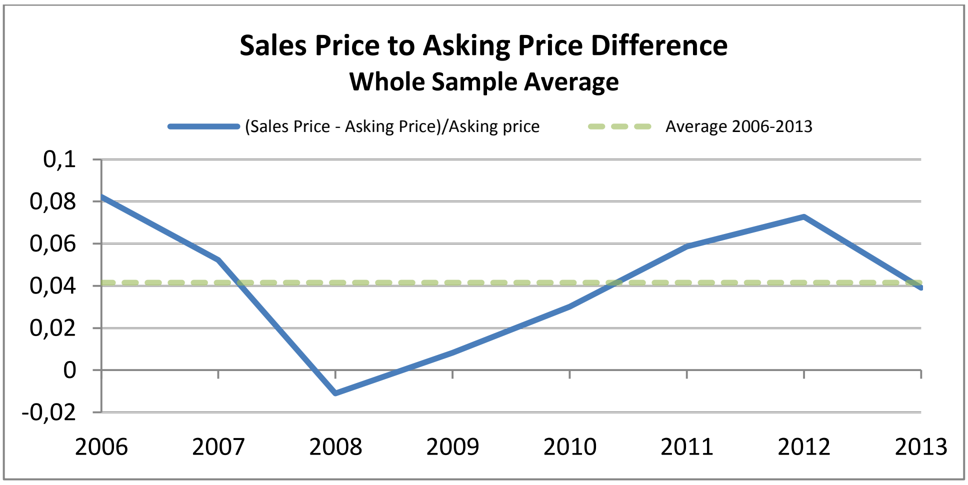

Figure 5 – Difference of Final Sales Price From Asking Price as Ratio of Asking Price

Hence, Figure 5 tells us the magnitude of how much over the asking price the sales price ended up, expressed as a percentage of the dwellings asking price.

We see sizable differences over time, ranging from 8% in the boom year of 2006 turning into -1,1% in the downturn year of 2008. The percentage of total apartments that sold for more than asking price is always more than half the sample size, except for the year of 2008. The variation in the sample ranges from 35% to 81% of the dwellings being sold for more than asking price. The percentage that sold for exactly the asking price is, perhaps surprisingly, low and varies between 6% to 10% of total transactions. These are in and of itself no indications of sentiment in the market, however we should take note of the tendency that dwellings are, on average, being sold for more than asking price. It seems like a puzzle to try to explain such behavior in a rational framework, if the asking price is to be interpreted as the willingness-to-accept on the behalf of sellers. However there could be strategic components to the asking prices, and they might also be affected by the value evaluation. Those aspects will be further highlighted in the empirical analysis, found in section 3 of this thesis.

1.5 A note on Markets, Experience and Mitigation of Behavioral Biases

As has been repeatedly noted through the theoretical part of this thesis, it is not necessarily a causal connection between the correction of behavioral biases and market exposure. However, a common conjecture in traditional theory is that market exposure, experience, or both, will in fact mitigate the biases which are found at an individual level. It is assumed that in the aggregate, behavioral biases cannot exist. As previously mentioned, Genesove and Mayer (2001), Engelhardt (2003) and Bokhari and Geltner (2011) all find that loss aversion carries over to affect the final transaction prices in the market. The analysis of Hott (2012), which is described in Appendix A, also suggest that herding effects are evident in the aggregate. Also, we have discussed indications of charm pricing having a potentially positive effect on final sales prices (Allen & Dare, 2004), and that round numbers can be shown to be greatly overrepresented amongst final sales prices (Pope et al., 2014). Thus, the argument pertaining to the ability of markets to mitigate behavioral biases is still very much debatable. See the end of Appendix A for a more comprehensive overview of this issue.

The next chapter marks the beginning of the empirical part of this thesis. Here, I will further delve into the effects of charm pricing and round numbers. However, as the data also contains value evaluations by professional surveyors I will start out the analysis with an inquiry into how these are formed. Potentially, they can act as anchors in the market for housing in Oslo.

2 The Oslo Housing Market - Empirical Analysis

2.1 About The Data

The dataset which I have obtained, covers housing transactions carried out in Oslo, during the period 01.01.2006-31.01.2014. The data is limited to dwellings which are defined by Statistics Norway to be of the “freeholder” type (“Selveier”), and therefore does not include any information about the developments in the housing cooperative market (“Borettslag”), or other such types of housing. The total dataset is comprised of 65 969 transactions. As the year 2014 only holds approx. 600 observations, it is to a limited extent in which we can explain developments in that specific year. It is also worth noting that the dates above are the period for which the *actual sale* went through. There are 242 observations that were enlisted in the market *before* 01.01.2006.

Another issue that possibly has a large impact on the sample is the fact that the data only contains transactions that were finalized. Therefore, we do not observe those dwellings which were listed in the market and then later withdrawn. The possibility of house owners to exit the market makes it difficult to assess empirically, how many dwellings actually make up the entire market and which could potentially be sold. The rate of entry and subsequent withdrawal could give an indication of the level of disagreement between sellers and buyers. The rate of exit could thus be interpreted as a gap between willingness to accept (WTA) and willingness to pay (WTP). However, because of lack of data this WTA-WTP gap cannot be measured for this sample.

According to Statistics Norway’s (2013) account of the real estate market in Oslo, the entire mass of inhabited freeholder dwellings in Oslo tallies to approximately 110 000 units. The total dataset acquired for this study is comprised of 64 969 transactions, e.g. 59% of the total housing mass was transacted over the course of the sample. Even if we assume that each individual dwelling is sold only once, i.e. no reoccurring sales, the data only covers a limited set of dwellings found in the municipality of Oslo. So even though OECD finds that Norway and the Nordic countries in general are amongst the most frequent movers (Andrews & Johansson, 2011), it is safe to say that most people do not change dwelling in the short to medium term. The data was retrieved from Eiendomsverdi AS which is a commercial company focusing on developing statistics and automated valuation models of real estate. A more thorough description of the dataset and its quality is to be found in Appendix C.

2.2 Data Cleaning Procedure

To shape the dataset into a functional form which allows the succeeding analysis of charm pricing, round numbers effects and loss aversion, I restricted the sample to those observations where none were missing; registration date, public registration date, salesprice, value valuation, living area (m^2), asking price, build year and city district. 11 000 observations were thus dropped, mostly due to lacking public registration date (approx. 3000) or value evaluation (approx. 7000). This will then allow for analysis through a hedonic pricing model and OLS regression.

I generate the variable TOM (time-on-market) as the difference between registration date ("RegDate") and the actual sales date ("ActualSaleDate"), the duration is then expressed as number of days. There might be some self-censoring in the sample when it comes to time on market, as sellers can pull listings from the market and re-list again. This will bias the time on market variable downwards. However, the TOM-variable does not play a crucial part in the analysis, as it is found to be a very noisy measure. This is discussed further in section 3.2.2 Charm Pricing Regression Analysis.

42 observations are dropped based on their location, being in the nearby forests of Oslo ("Marka"). They are technically speaking within the city limits, but are both older and larger than the average type of dwelling. I would argue that they are to be considered recreational properties, not primary dwellings. As such, they are dropped from the sample. A couple of observations were also deleted as they are located outside the municipality (Siggerud).

A handful of observations were missing the city-district variable, but had postal codes which then were used to match the observations to the right city-district manually. This was less than 50 observations.

The "renovated year" variable was cleaned in a way such that occurrences like 20022006 were recoded to only hold the last observed date, ie 2006. Entries where "renovated year" was the same as the build year were set to missing "renovated year". Observations where values were greater than 2015 were set to missing. Please see the variable lists included in Appendix C for summary statistics and an explanation of all variables in the sample.

The owner of the compiled dataset, Eiendomsverdi AS, has automated procedures to eliminate entries where obvious mistakes are detected in square meter price, number of rooms, size of the dwelling etc. The entire dataset stems from manual data, input by real estate agents into a common database. These transactions are then subsequently matched with the official records of the dwelling, when the transaction has been processed at the government registry. Then the automated trimming by Eiendomsverdi AS' system is conducted. Therefore we cannot say that the data is completely without errors. However, the impact of the erroneous entries should at least have been minimized.

Further censoring of the sample is perhaps warranted as I have discovered some remaining false entries, such as typo's in the salesprice, value valuation, asking price, livingarea etc. In a few observations we can clearly see indications of such when salesprice is 3 500 000, asking price is 3 390 000, but value evaluation is registered as 3390. Or instances where asking price and value evaluation are 12 900 000 but salesprice is 1 300 000, suspecting thus that a zero is missing in the salesprice. Those kind of "fat-finger mistakes" are perhaps most likely for high value properties (price>10 000 000), where zeroes are hard to keep track of.

However, as this procedure is time consuming and not readily done based on any pre-established objective criteria, I have decided against it. In the end, it is likely to only involve only a small percentage of the sample, and thus presumably will not affect the results in a decisive way. Alas, some degree of measurement error is likely to be present in the data.

The core dataset which is fit for analysis purposes ultimately consist of 51 858 out of the 65 969 original observed transactions in Oslo for the period 01.01.2006-31.01.2014

2.3 The Average Dwelling

We can make use of all the means for the variables to inform us about how the hypothetical average dwelling in the sample looks like:

The average dwelling in the data set is an apartment which has 89 square meters of living space, it has 2 bedrooms, is built around 1955, located on the 3rd floor (Norwegian numbering; 1st floor = ground floor), in the borough of Frogner, sold in the year 2013, after spending 25 days on the market and cost 3.5 million NOK. However, to the informed reader it should be clear that no such apartment actually exist with all these particular attributes. For instance, an apartment of 89 square meters in Frogner usually sell for 4.4 million in the datasample. Therefore we must keep in mind that the average dwelling is a useful hypothetical construct which is put together to quickly summarize the diversity of the data into one single entity, however it is not representative of all of the specific subsamples, when those are assessed separately.

Table 1: Type of Dwelling

Variables	Apartment =«Leilighet»	Detached house = «Enebolig»	Row-house =Rekkehus»	Semi-detached house (duplex) = «Tomannsbolig»
Number of observations	41 233	4522	3042	3105
Mean living area	70 m^2	191 m^2	132 m^2	149 m^2
Mean sale price	2.985.558	6.754.531	4.527.406	5.369.821
Mean asking price	2.880.766	6.651.999	4.363.855	5.185.263
Mean value evaluation	2.944.792	6.788.886	4.434.842	5.274.467
Mean difference of: (final sale price - asking price)	104.792	102.532	163.551	184.559
Mean difference of: (final sale price - value evaluation)	41.020	-34.355	92.564	95.355
Mean difference of: (asking price - value evaluation)	-64.025	-136.887	-70.987	-89.204

From the geographical distribution of housing transactions, the data indicate that the boroughs Frogner, Grünerløkka, St. Hanshaugen and Sagene are responsible for almost 50% of all of the transactions observed in the data. The central boroughs thus transact far more often than other boroughs, and are overrepresented in the sample. More on this, and the spatial distribution of dwellings in Appendix C.

In section 3, I will focus on the relations between value evaluations, asking prices and final sales prices. Thus, it is helpful to keep in mind some of their respective attributes:

The value evaluation found in the sample is set by a professional surveyor, after conducting a check on-site for the dwelling in question. Thus, any variables that are unobserved in the data, but evident to the surveyor will likely be integrated in the surveyor’s estimate of market worth. Surveyors might have an incentive to give generous estimates, as their business is largely based on referrals from realtors. An attempt to account for this is beyond the scope of the data and this thesis.

The asking price is set by the seller, most commonly with the aid of a realtor. As realtors often have more knowledge of the current market conditions than the seller himself, it is plausible that the realtor’s advice for design of listing price is followed in most cases. But again, this cannot be tested with the data.

The final sales price is determined by the market, which in Norway has the form of an auction, most similar to an ascending-bid auction type (English auction). From 2014 and onwards it has been required that bids are submitted electronically. The institutional and legal framework for the housing market is potentially a decisive factor for the behavior observed in the market. The

Norwegian housing market differ from the U.S. market in a number of ways, however only a select few are noted here:

- Strategic default (jingle-mail) is not commonplace like in the U.S. See Holm and Astrup (2009) for more on the Norwegian institutional setting in relation to default.
- In Norway, only the seller solicits the services of a realtor, as opposed to the U.S. where both seller and buyer usually have their realtors bargain for them. Thus, the asymmetry of information and negotiation experience is perhaps expected to be larger in the Norwegian setting.

Now, let us move over to some summary statistics of the relevant pricing measures:

The mean asking price in the sample was 3.4 million kr (or 3.490.000 when charm pricing is being utilized), and the average difference of final sales price from asking price was 113 000 kr above asking price. That is, 3,3% of the value of the average apartment in the sample, ($\frac{113\ 000}{3\ 433\ 484}$ = 3,3%).

The average difference in asking price from value evaluation was -72 238 kr, meaning that the list price, on average, was posted lower than the assessed value, as given by the professional surveyor. We also find a large standard deviation of 181 248 kr, implying that there is a considerable amount of variation in the data.

The average difference in sales price from value evaluation was 40 775 kr, meaning that the average assessed market price was a bit undervalued, but only to the extent of 1,15% of the worth of the average dwelling ($\frac{40\ 775}{3\ 546\ 295} = 1{,}15\%$). The Oslo housing market has mostly seen year on year price increases over the years in the sample, and the finding that the mean sales price is higher than the mean value evaluation could suggest that the surveyors do not sufficiently adjust to current (booming) market conditions quickly enough, when giving estimates of market worth. The standard deviation of the difference in sales price from value evaluation is quite sizable, at 411 683 kr, indicating that the point predictions of an assessor can vary substantially from the final sales price.

In table 1, we can better assess the variation in the data which is categorized by the type of dwelling. First we should note the overwhelming majority of apartments, as type of dwelling, being transacted in Oslo. Most people in Oslo live in apartments, and their transaction volume is almost 80% of the entire sample. If we think of the difference of asking price from value evaluation as "under-pricing", then all types of dwellings are under-priced, on average. While apartments are "under-priced" more in percentage terms than detached houses (2,22% to 2,06%), the higher average price of detached houses make the under-pricing of these dwellings larger in absolute prices. Thus, in relation to their own average asking prices, the apartments have the strongest degree of under-pricing when they register in the market.

Furthermore, the fact that detached houses are the only type of dwelling that has a negative gap between final sale price and value evaluation, on average is worth noting. This implies that for this specific category of housing the value evaluations are higher, on average, than the final sale price. Thus, the professional assessors tend to overestimate the worth of this category of dwellings in particular.

Perhaps this is due to the dissimilarity of houses, which translates into difficulty in assessing a large house and property. After all, there are fewer similar objects in the market by which to compare and assess market value. The relative similarity of apartments might make it easier to assess the market value, as they appear more frequently, and assessors therefore learn to adjust their estimates quickly. In theory, they should not need to learn, they are rational and can calculate of course, however to explain the data, a story of adaptive learning seems fruitful. Another plausible interpretation is that the average measures of prices for detached houses is more susceptible to large outliers, as their price range is wider than that of apartments. We will return to this issue in section 3.1 in particular, and chapter 3 as a whole is devoted to further investigation of the complex relations between value evaluations, asking prices and final sale prices.

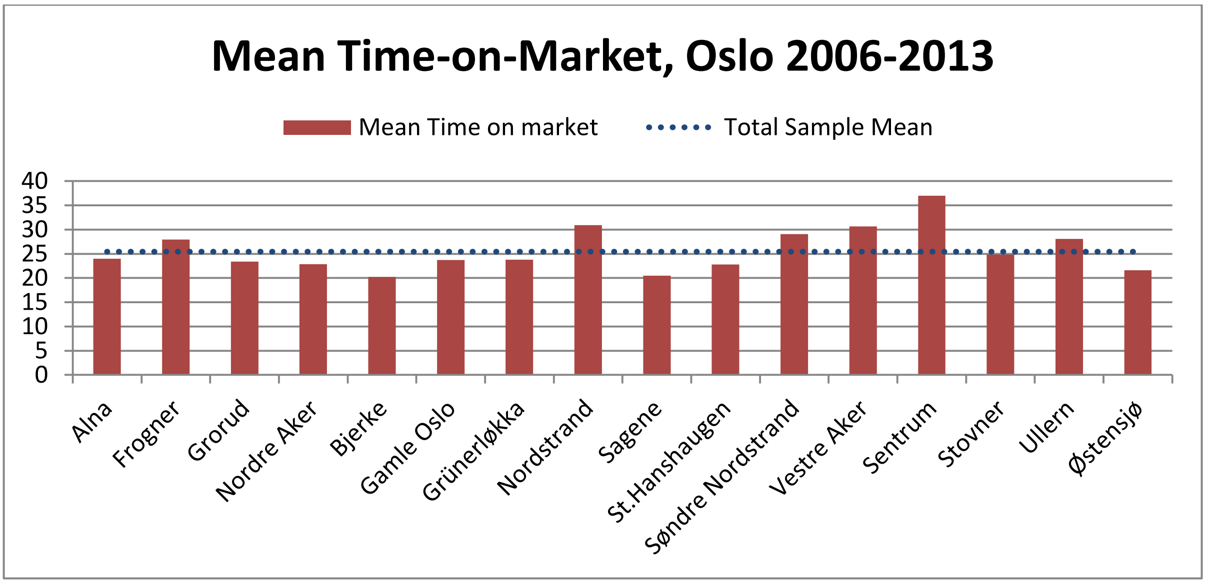

Figure 6 – Mean Time-on-Market

In Figure 6, I have graphed the differences in time-on-market, a measure of how fast the dwellings are sold, for the different boroughs. Here we find some puzzling results, as “Bjerke” has the quickest turnover of dwellings, with an average time-on-market at just above 20 days. In the other end of the scale we find “Sentrum” as the slowest borough to sell in, but with only 154 observations across 8 years any statistical inference is of limited reliability. “Frogner” has quite a high mean of time-on-market, which is surprising given that it holds 20% of all transactions, and housing demand for this specific borough seems to be high.

It should be noted however, that time-on-market in the range of 20-30 days should be considered quite fast. There is considerable variation in the time-on-market within the different municipalities in Norway. As Oslo is one of the fastest growing cities in the country, the time-on-market has been comparatively low. If we look to the U.S. housing market, which has recovered since the financial crisis but is still below peak in terms of prices, the average listing time the past 5 years has been above 100 days (Zillow, 2015). In the UK, the average time on market has varied between approx. 70 days to 45 days over the years 2010-2014 (Hometrack, 2014).

Now, let us have a look at how variation in value evaluation and asking price can have an impact on the final negotiated house price.

3 The Interlinkages Between Sales Price, Asking Price and Value Evaluation

In the dataset I have acquired for this analysis, there are 3 indicators of a dwellings market worth; the value evaluation set by the professional surveyor, the asking price set by the real estate agent/owner-occupier and lastly the final transaction price. In most studies, it is common to only observe final transaction price and asking price. The value evaluation thus gives us an “extra degree of freedom”- sort of speak, and it is why the intent of this section is to dissect the connections between the three price measures. In the following analysis, ordinary least squares (OLS) estimates are presented, unless otherwise stated. Throughout the regression analysis the coefficients’ significance levels are calculated using robust standard errors, unless otherwise stated. The Huber/White standard errors which are heteroscedasticity-consistent and easily implemented in Stata are the preferred option as the data show clear indications of heteroscedasticity. Log-log and log-linear specifications were considered, however as they showed similar results as the linear specification, the latter was preferred. In all of the reported regressions, the omitted category for dwelling type is “detached houses” and “Østensjø” for the borough dummies, thus serving as baseline for the estimated coefficients.

3.1 The Value Evaluation – An Unbiased Estimate?

Is the assessed value that the professional surveyor gives for each property an unbiased estimate of the market value for the dwelling?

A simple OLS regression was conducted for the full sample, and by type of dwelling of the form:

$$\text{Salesprice} = \beta_0 + \beta_1(\text{Value Evaluation}) \qquad \textbf{(1)}$$

We see from Table 2 that the assessors’ value evaluations are good indicators of market value. For the full sample, the value evaluation explains 96.5% of the total variation in sales prices. In the case of detached houses, the value evaluation explains less of the final sales price, as compared to the other types of dwellings. This is in line with the proposed interpretation of a more heterogeneous market for detached houses, which makes it more difficult for the assessors to estimate the market worth of that type of dwelling. However, the standard errors for detached houses are comparatively quite low, perhaps indicating that row-houses and semi-detached houses are more heterogeneous.

Table 2: Simple OLS Regression of Salesprice on Value Evaluation

	β-coefficient from OLS regression	**Robust standard errors**	**R^2**	**Number of Observations**
Full sample	.95***	.0025	.9654	51858
By Type of Housing				
Apartment	.95***	.0030	.9641	41233
Row House	.96***	.0082	.9444	3042
Semi-Detached House	.95***	.0092	.9312	3104
Detached House	.89***	.0070	.9346	4479

* p<0.1; ** p<0.05; *** p<0.01 Robust standard errors are the Huber/White-estimators of variance

Even though the surveyors are quite accurate on average, it is interesting to see which property characteristics are relevant to explain the value evaluation itself. As far as the author knows, a large dataset which holds both value evaluations by professional surveyors and sales price, has yet to be analyzed. This gives us the opportunity to assess which factors are incorporated in the surveyor's market value estimates, and which are not accounted for. In most cases the analysis does not include a value evaluation, and thus may partly fail to control for unobserved characteristics of the dwelling (examples are; (Allen & Dare, 2004; Beracha & Seiler, 2014; Palmon et al., 2004)). The following description can thus give us an indicator of how much of the variation in data, which can be ascribed to previously unobservable characteristics. First, let us look at which property attributes which can explain the value evaluation.

The specification is as follows:

Value Evaluation = **β**(Living Area, Build Year, Actual Sale Year, Actual Sale Month, Apartment Dummy, Row House Dummy, Semi-Detached House Dummy, City Borough Dummies)

Where **β** is a vector of the regression coefficients, including an intercept The time trend is made up by two components, actual sale year which runs from 2006 to 2014, and actual sale month indicating which month the dwelling was sold (1 through 12).

Table 3: Regression Results of Value Evaluation on Dwelling Characteristics

Dep var: Value Evaluation	Coefficient	Robust Standard Error	t
Livingarea	35,975.8***	305.7	117.67
Build_Year	4,088.5***	208.9	19.57
Actual_Sale_Year	187,923.2***	1,823.0	103.08
Actual_Sale_Month	16,785.0***	1,289.9	13.01
Dummy variables:			
Apartment	58,327.5	37,913.2	1.54
RowHouse	-133,987.0***	32,471.2	-4.13
SemiDetached	-67,433.9*	37,780.7	-1.78
Alna	-367,052.3***	29,075.6	-12.62
Bjerke	260,140.3***	23,182.0	11.22
Frogner	1,681,923.2***	25,791.8	65.21
Gamle_Oslo	675,252.3***	21,105.1	31.99
Grorud	-493,664.5***	45,500.1	-10.85
Grünerløkka	862,202.1***	21,889.0	39.39
Nordre_Aker	1,164,602.8***	24,168.5	48.19
Nordstrand	745,236.7***	29,364.9	25.38
Sagene	898,041.7***	21,055.5	42.65
Sentrum	1,337,650.0***	42,224.7	31.68
St_Hanshaugen	1,251,024.9***	22,990.3	54.42
Stovner	-797,738.2***	27,400.3	-29.11
Søndre_Nordstrand	-815,395.1***	25,695.2	-31.73
Ullern	1,248,589.0***	26,466.0	47.18
Vestre_Aker	1,261,297.0***	28,227.4	44.68
_cons	-386,394,951.6***	3,686,743.4	-104.81
F statistic	3,132.98		
R-squared	0.81		
Number of Observations	51,858		

* *p*<0.1; ** *p*<0.05; *** *p*<0.01 Robust standard errors are the Huber/White-estimators of variance

Table 3 is the results of a hedonic regression to see which factors; such as geographical location, build year, size of dwelling and other characteristics, can explain the value-evaluation given by the surveyor. The omitted category for dwelling type is “detached houses” and “Østensjø” for the borough dummies, thus serving as baseline for the estimated coefficients. We see that all included variables are highly statistically significant and seem reasonable given the general differences in price levels across the different boroughs and dwelling types. All coefficients have the expected signs, except the indicator for apartment, which is quite surprisingly not statistically significant. The result also shows that the effect of semi-detached houses is only significant at the 10% level.

We note that there is still a large portion of unexplained variation in the data, which suggest that there are still other factors that the value evaluation incorporates, which is not easily controlled for. Even when conducting a reduced sample regression with observations that include more specific dwelling characteristics, such as; floor of dwelling, year of renovation, number of bedrooms etc., the level of unexplained variation in the data remains. It is therefore likely that simple metrics are not a perfect substitute for a hands-on survey of a dwelling. There is after all many things about a dwelling that are perhaps difficult to quantify, such as the state of, or quality of a dwelling and light conditions.

Now we can move on to see how well the sales price is explained by the value evaluation. We can augment the value evaluations with the observed property characteristics to see if the assessors do or do not sufficiently incorporate all the relevant information into their estimates. If the assessors' value evaluations correctly weights the different property characteristics, then we would expect to find that the coefficients of those added variables would be negligible, as the information is already accounted for through the value evaluation.

Table 4: Regression Results of Sales Price on Value Evaluation and Dwelling Characteristics

Dep.Var: SalesPrice	Coefficient	Standard Error	t
Value_Evaluation	0.9***	0.0	142.28
Livingarea	1,874.9***	218.3	8.59
Build_Year	94.5*	54.7	1.73
Actual_Sale_Year	17,822.4***	1,253.4	14.22
Actual_Sale_Month	-7,320.5***	520.7	-14.06
Dummy variables			
Apartment	-155,375.2***	14,576.9	-10.66
RowHouse	-8,482.7	13,209.7	-0.64
SemiDetached	23,221.9	15,826.0	1.47
Alna	-108,192.0***	11,010.4	-9.83
Bjerke	-23,552.9**	9,768.2	-2.41
Frogner	52,880.4***	12,595.1	4.20
Gamle_Oslo	-15,183.8	9,531.5	-1.59
Grorud	-145,054.1***	14,328.0	-10.12
Grünerløkka	-13,331.3	10,190.2	-1.31
Nordre_Aker	145,021.1***	13,136.6	11.04
Nordstrand	-16,726.6	13,247.5	-1.26
Sagene	22,947.3**	10,067.0	2.28
Sentrum	-79,239.8***	19,041.2	-4.16
St_Hanshaugen	40,443.7***	11,324.0	3.57
Stovner	-170,136.6***	10,676.8	-15.94
Søndre_Nordstrand	-213,748.3***	10,544.2	-20.27
Ullern	37,544.2***	13,764.5	2.73
Vestre_Aker	-6,848.6	13,950.0	-0.49
_cons	-35,587,456.6***	2,552,647.7	-13.94
F statistic	18,489.59		
R-squared	0.9675		
Number of Observations	51,858		

* p<0.1; ** p<0.05; *** p<0.01 Robust standard errors are the Huber/White-estimators of variance

We note that the value evaluation is still a good estimate of a dwellings market worth, however as it's coefficient now is notably lower than before, it tells us that the value evaluation is not entirely incorporating all relevant information in a sufficient way. When holding the value evaluation constant, we see that there are systematic and statistically significant differences between the different boroughs, which might indicate that the surveyors do not sufficiently account for the effect of the location on price. It also follows from the results that surveyors tend to underestimate the effect the size of the living area has on price. The apartment indicator is now the only dwelling type indicator that is statistically significant, and it is negative.

Overall, we see that the R^2 only increases incrementally from the initial simple regression of value evaluation on sales price. The R^2 of 0.9654, to be found in table 2, increases marginally to 0.9675 as we include a dwelling's characteristics in the regression (table 4). It is therefore reasonable to infer that the value evaluation and the observable characteristics of a dwelling both contain much of the same information-signal, which is relevant to explain the final sale price of a dwelling. However, as the coefficients on most of the property characteristics are highly statistical significant we can say that they refine the information which was already contained in the surveyor's estimate. Still, there are residuals that both value evaluation and observable characteristics cannot account for. Thus, we do not have a perfect account of the variation in the data. However, the unexplained variation is now quite small, and it is within reason to make use of these data for modelling purposes.

3.1.1 The Clustering of Value Evaluations

Figure 7 gives us an overview of the distribution of value evaluations, across the range of 1 million to 6 million kr. It shows a marked influence of clustering at round numbers ending with 50 000, 100 000 or on million markers.

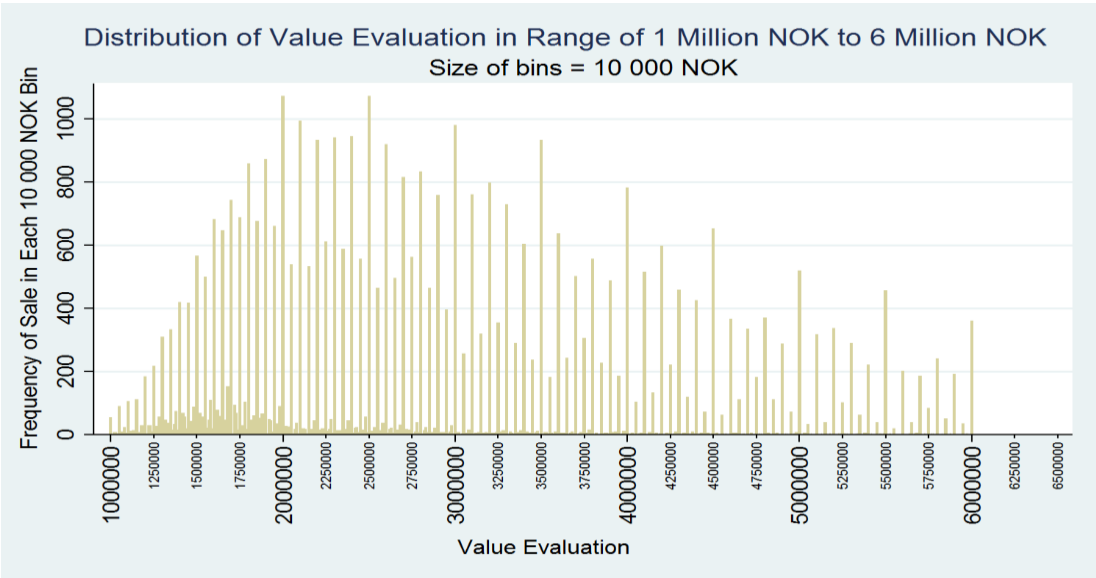

Figure 7 - Distribution of Value Evaluations

To get a better impression of the level of clustering, the histogram in Figure 8 tells us that the clustering is strongest at price points which are multiples of 500 000kr, while multiples of

100 000kr and 50 000kr follow close behind. The extremely low frequency of dwellings with prices that are not cleanly divisible by 50 000kr is evident by the lack of mass found in these price bins.

It seems that the convenience rounding story has some merit. Perhaps surveyors do not want to give too precise market value estimates, and thus they only make use of a coarse pricing grid when assessing a dwellings value. We can of course only speculate as to why this is the case, but a story of convenience rounding certainly fits with the data.

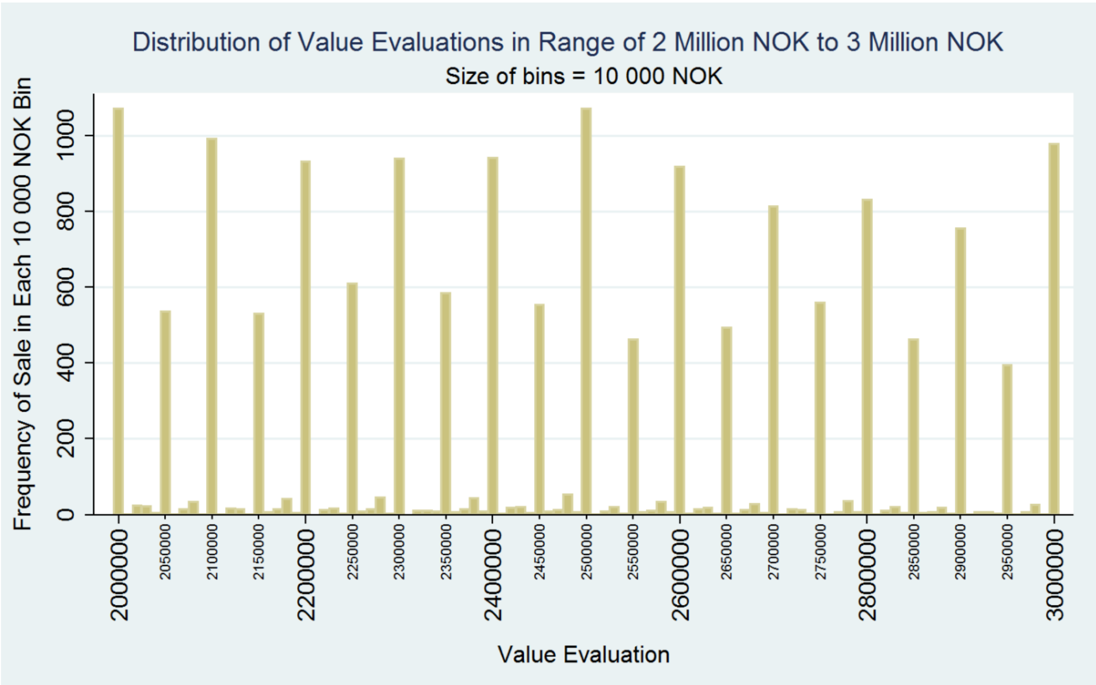

Figure 8 - Value Evaluations - Clustering at Round Numbers

The round numbers bias which surveyors seem to be subjected to, displays a behavior that is changing across different price levels. The clustering at round numbers that ends with 50 000kr is strong for the price level between 2 and 3 million kr. However, when we look at the price range between 9 and 10 million kr, there is almost no value evaluations at all that make use of the prices ending with 50 000kr. What is found is a reliance on the use of half-million and million markers, and to a lesser extent the use of prices ending with multiples of 100 000kr. Therefore it seems reasonable to describe the coarseness of the pricing grid that the surveyors make use of to price a dwelling, as being relative to the price range of the dwelling itself. That is, for the low price range (up until about 5 million kr) there is extensive use of prices ending in 50 000kr, thus differentiating between the different dwellings at a 50k detail level. However, for the medium price range (value evaluations above 5 million kr), there is a decreasing reliance on the prices ending with 50 000kr, and a notable more extensive use of value evaluations ending with 100 000kr. At the high price range (above 10 million kr) there is almost an exclusive reliance on 500 000kr markers and million markers to differentiate between the dwellings. Therefore, it seems like the coarseness of the surveyors' pricing grid moves inversely with the price level. It migrates from a high level of detail/accuracy when prices are low, to a low level of detail/accuracy when prices are high.

We will later on, in section 2.4, assess how the value evaluation might serve as an anchor in the decision-making process of the participants in the housing market.

3.2 Asking Prices – Charm Pricing:

What is an asking price? It might seem like a simple question, which we would like to answer in a simple way. Unfortunately, it does not have such a straight-forward interpretation. The asking price is the price which the seller set on his dwelling when it is listed for sale in the market. So far, so good, but it is when we want to interpret the price we run into ambiguity. Is the asking price to be understood as the willingness-to-accept? Is it a strategic information signal in the game of housing allocation? Is it the starting point of negotiations? Can the design and level of asking price have a positive effect on the final sales price, so called charm pricing? The following analysis outlines a less than simplistic answer, with a focus on the latter question.

Amongst all the possible asking prices in the observable range of our dataset, from 490 000 kr to 35 000 000 kr, we only have 865 unique values. Meaning that there are 34 510 000 possible values that could be chosen as asking price (if we limit ourselves to integers), which have not been used in the real estate market in Oslo over the period of 2006-2014. That is a tremendous 99.75% of the possible range which is not being utilized! This sort of clustering is found in both value evaluations, final sale prices and as we will discuss further here, asking prices.

While that may be the case, one could argue that in the price range from 10 million to 35 million there are only a few handfuls of transactions, so that the whole range should not plausibly be filled by such a low number of observations. However, if we look at one of the most common ranges of dwelling prices, that is 2.5 to 3.5 million kr, which holds roughly 23% of our entire sample, the clustering of asking prices is still evident. Out of the 1 million possible asking prices, we only observe 127 unique values. Meaning that, 98.73% of the possible asking prices are not being used. If we allow for a simple story of convenience rounding, so that market participants only deal with multiples of 1 000kr, then still only 12,7% of all possible values are being used.

Over the entire sample, we find that the correlation of asking price and value evaluation is 0.9968. It seems to be true that people, or at least the realtors they hire, to a large extent follows the value evaluation of the professional surveyor when setting the asking price. This seems to be a reasonable approach to the design of listing prices, as long as the value evaluations are good estimates of market value.

As we can read from Table 5, the most common design of asking price is to set it exactly equal to the value evaluation, and 41,5% of the dwellings exhibit this sort of pricing behavior. Out of the listing prices which are different from the value evaluation, the most frequently used are from 10 000kr below the value evaluation to 200 000kr below value evaluation.

Table 5: Most Common Listing Prices; As Measured by Difference From Value Evaluation

(Asking price – Value evaluation)	Frequency (% of total sample)	(Asking price – Value evaluation)	Frequency (% of total sample)
0	41,5 %	-210 000	3,0%
-10 000	12,7 %	-100 000	2,6%
-110 000	8,4 %	-160 000	2,0%
-60 000	7,0 %	-150 000	2,0%
-50 000	4,9 %	-200 000	1,2 %
Total frequency of most common charm listing prices i.e. excluding (asking price = value evaluation): 43,8%			

A noteworthy aspect of the data is that only 0,84% of the transactions in the sample chose an asking price above the value evaluation. In this regard, the value evaluation seems to be setting the upper bound for asking prices in most cases.

3.2.1 The Clustering of Asking Prices

The histograms displayed in the Figures 9 and 10 are the same as those shown in the Figures 7 and 8, only this time it is the distribution of asking prices and not value evaluations. We can now evidently see that the clustering of prices are just below the round numbers that are multiples of 100 000kr. This is what we call charm pricing. Interestingly it seems as the charm pricing mechanism does not relate to the round numbers ending in 50 000kr. Perhaps it evokes a too detailed price grid that is traded off against the convenience of rounding?

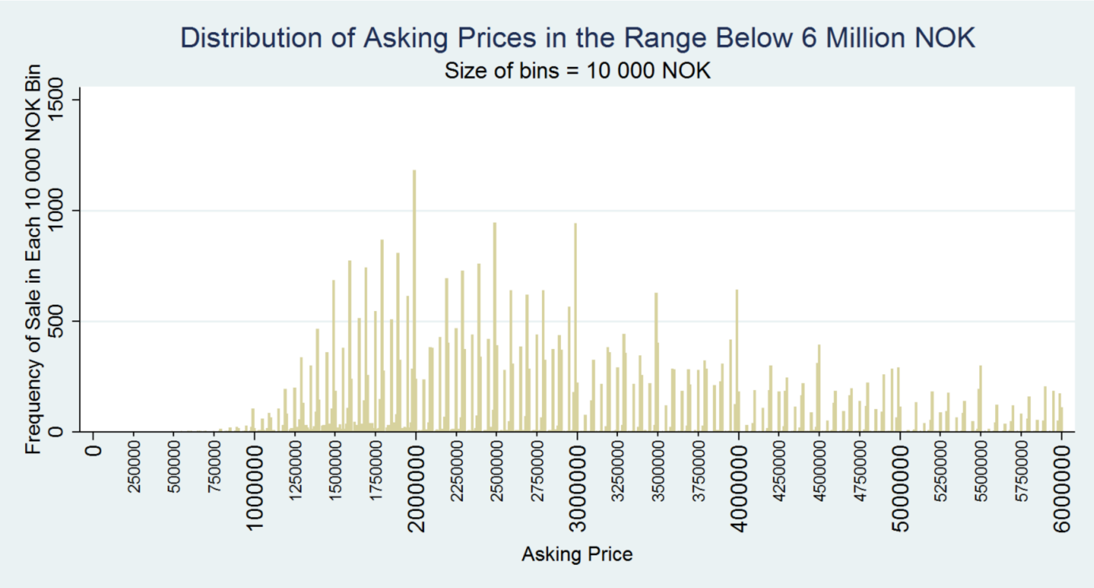

Figure 9 – Distribution of Asking Prices, overview

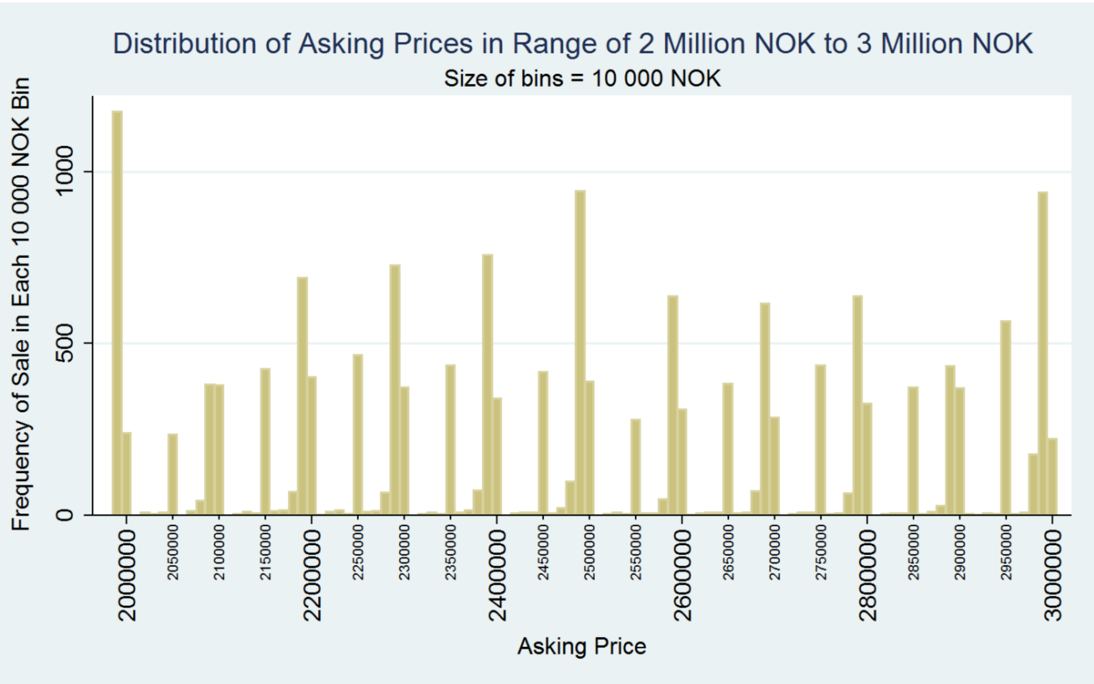

Figure 10 – Distribution of Asking Prices, Clustering at Charm Prices

From Table 5 it appears likely that the three out of the top four most common listing price strategies are designed such that they will yield a charm listing price. As we now know, the value evaluations tend to be in round numbers. Thus subtracting either 10 000kr, 110 000kr or 60 000kr will yield a listing price in the form of 1 990 000, 1 890 000 or 2 940 000, if the value evaluation was 2 000 000kr. However the subtraction of 60 000kr from value evaluation is almost exclusively being used for dwellings where the value evaluation ended with 50 000kr, thus yielding a charm asking price in the form of 1 990 000. The occurrence of the -60 000 from value evaluation is almost entirely found in the price range below 6 million, again perhaps indicating that the coarseness of the pricing grid increases as the nominal values increases.

In fact, most of the studies described in this paper has been conducted in the American markets, where values are denominated in dollars. If there was no such thing as charm pricing effects and round numbers bias, then we should observe the charm pricing and round numbers bias for the dollar equivalent value, stated in Norwegian currency terms. E.g. if there was an effect of housing prices ending in \$9 999, then the equivalent in Norwegian kroners at the current exchange rate of 7,4761kr/dollar would be 74 753,5239kr. This claim is rejected by the data. Thus in this way, the data this thesis' presents further validates the findings of Allen and Dare, and PPS.

3.2.2 Charm Pricing Regression Analysis

Let us further investigate the design of asking prices, and whether or not we can classify them as charm pricing.

In Allen and Dare (2004) they identify charm listing prices as the occurrence of listing prices ending with \$500, \$900, \$4 900, \$5 000, \$9 000 and \$9 900. Their results show that all of these listing price designs have a positive effect on the final transaction price, although their magnitude varies across the different price segments of the housing market. Dwellings that transacted in the range of \$300,000 to \$1 million have the strongest price increase for listing prices ending with \$5000. For dwellings worth in the range of \$ 200,000 to \$300,000 the largest positive effect is for listing prices ending with \$ 9 000. In the consequent analysis, we will closely follow the empirical approach of Allen and Dare. However, there is a matter of subjectivity in the conversion of the charm-prices identified by Allen and Dare, to properly apply it to the Norwegian housing market.

As there is no agreed-upon norm of what is strictly considered a charm-price and what is not, we need to go with intuition and logical reasoning when choosing the listing price designs which are to be considered charm-prices in a Norwegian context. I propose the following designs of listing price to be considered as charm prices:

Listing prices ending with 50 000kr, 90 000kr, 490 000kr, 900 000 kr, 990 000kr.

The dummies constructed for these listing prices are mutually exclusive, that is a listing price of 1 990 000, does only give an indicator equal 1 to the 990 000kr charm dummy, and not the 90 000kr dummy or the 900 000kr dummy. A listing price of 5 490 000 yields an indicator dummy equal 1 for the 490 000kr dummy, and not for the 90 000kr dummy. In this way the 90 000kr dummy picks up all *other* charm listing prices ending in 90 000, e.g 2 190 000kr or 3 890 000kr.

To control for other listing price designs and check the robustness of the charm listing price-effects, I also construct dummies for round number pricing. Listing prices ending with *00 000kr, 500 000kr or 1 000 000kr are identified as round numbers. The round number pricing dummies are also constructed in a mutually exclusive way, analogous to the charm pricing dummies. To be explicitly clear; A dwelling cannot have both an indicator for charm pricing and round number pricing at the same time. The order of priority is such that a listing price ending with 900 000kr, is identified as charm pricing, and not a *00 000kr round number. See Table 6 for a full description of the design of dummy variables, which is arranged in hierarchical order after which dummy dominate the others when there is a conflict.

Table 6: Variable Definitions for Round Numbers and Charm Price Dummies

CD990k	**Dummy variable indicating that the asking price ends with 990 000** **e.g. 4** 990 000**, 2** 990 000 **etc**
CD900k	Dummy variable indicating that the asking price ends with 900 000 e.g. 1 **900 000**, 7 **900 000** etc
CD490k	Dummy variable indicating that the asking price ends with 490 000 e.g. 2 **490 000**, 5 **490 000**
CD90k	Dummy variable indicating that the asking price ends with 90 000 e.g. 2 3**90 000**, 6 1**90 000** etc
CD50k	Dummy variable indicating that the asking price ends with 50 000 e.g. 1 7**50 000**, 4 4**50 000** etc
Dmill	Dummy variable indicating that the asking price ends with * 000 000 That is on a million marker exactly. e.g. 1 **000 000** or 5 **000 000** etc
D500k	Dummy variable indicating that the asking price ends with 500 000. That is, exactly on a half million marker.
D100k	Dummy variable indicating that the asking price ends with *00 000. That is, on a hundred thousand marker exactly. e.g. 1 8**00 000**, 3 4**00 000**, 6 **700 000**, 9 **200 000**, etc **<u>Except:</u>** • asking prices ending with 900 000 which are categorized as CD900k. • asking prices ending in 500 000 which are categorized as D500k • asking prices ending on the million mark exactly, which are categorized as Dmill.

The chosen charm dummies all seem to be reasonable to consider as charm-prices, however the 50 000kr marker is likely to reflect both a degree of charm pricing, and the tendency of sellers to set asking price equal to value evaluation. The 50k dummy can thus be interpreted in both directions. More on this issue is found in the results section.

I would like to assess if there are differences in the charm pricing effect across different market segments. The market segments are defined by the magnitude of the final sale price. I divide the sample into 3 groups based on the following price ranges:

Group 1 = Sale price ≤ 3 000 000 kr

Group 2 = 3 000 000kr < Sale price ≤ 5 000 000 kr

Group 3 = Sale price > 5 000 000kr

These groupings are of course subjective in nature. However, they will help facilitate the analysis by neatly splitting the sample in three reasonably sized partitions. Group 1 is identified by a suffix "_1" to the charm listing price regression dummy, i.e. CD50k_1 is the charm pricing dummy for listing prices ending with 50 000, in the price range below or at 3 000 000 kr. Similarly, Group 2 and 3 are identified by the _2 and _3 suffixes to the relevant charm price and round price dummies for their price ranges (as defined in the text above).

Table 7 is a summary of how widespread the use of charm pricing and round number pricing is in the Oslo market for housing.

Table 7: Charm Listing Price and Round Number Listing Price in Proportions per Group.

Charm Listing Price	**Group 1** Listing price ≤ 3 000 000 n = 27032	**Group 2** 3 000 000 < Listing price ≤ 5 000 000 n = 15740	**Group 3** Listing price > 5 000 000 n = 9086
CD50k	0,263761	0,22967	0,18446
CD90k	0,322988	0,24028	0,103236
CD490k	0,059004	0,060038	0,048206
CD900k	0,019791	0,039072	0,085076
CD990k	0,059078	0,086595	0,060753
Total CHARM	0,724623	0,655654	0,48173
Round Number Listing Price			
D100k	0,131104	0,222173	0,294519
D500k	0,020531	0,048094	0,124367
Dmill	0,012541	0,022173	0,068127
Total ROUND	0,164176	0,29244	0,487013
Total non-CHARM & non-ROUND	0,111202	0,051906	0,031257

We note that charm pricing is the majority pricing strategy for this dataset, as it is more frequently used than round number pricing. The exception is the high price dwellings found in Group 3, where charm pricing and round number pricing have virtually an identical share. In the total sample, listing price strategies that are not round number or charm pricing constitute less than 8% of the transactions.

The regression model specification is as follows:

Salesprice = **β**(Charm Listing Price Dummies, Round Numbers Listing Price Dummies, Value Evaluation, Dwelling's Physical Characteristics, Time Trend, City Borough Dummies) **(2)**

Where **β** is a vector of the regression coefficients, including an intercept. The regressions are conducted separately for each of the three price groups.

Table 8: Charm and Round Numbers Listing Price Regression Results for Group 1: Salesprice ≤ 3 000 000 kr

Dep. Var: Salesprice	Coefficient	Robust Standard Error	t
CD50k_1	12,501.7***	3,679.9	3.40
CD90k_1	-1,537.7	3,611.8	-0.43
CD490k_1	7,670.3	5,414.2	1.42
CD900k_1	13,258.2*	7,841.8	1.69
CD990k_1	-392.5	5,802.9	-0.07
D100k_1	35,719.7***	4,291.8	8.32
D500k_1	33,950.5***	8,165.8	4.16
Dmill_1	53,733.6***	11,344.5	4.74
Value_Evaluation	0.8***	0.0	180.96
Livingarea	2,191.7***	124.7	17.57
Build_Year	24.5	35.3	0.69
Actual_Sale_Year	13,096.8***	606.6	21.59
Actual_Sale_Month	-3,022.9***	335.2	-9.02
Apartment	17,221.9	23,706.9	0.73
RowHouse	20,007.5	24,394.3	0.82
SemiDetached	6,013.0	26,240.9	0.23
Alna	-27,673.1***	7,565.4	-3.66
Bjerke	8,532.1	6,985.2	1.22
Frogner	49,278.1***	7,543.8	6.53
Gamle_Oslo	21,379.4***	6,709.0	3.19
Grorud	-36,877.8***	10,505.7	-3.51
Grünerløkka	23,473.1***	6,724.9	3.49
Nordre_Aker	31,155.2***	7,899.6	3.94
Nordstrand	-8,340.4	8,311.8	-1.00
Sagene	50,266.4***	6,996.5	7.18
Sentrum	-12,409.1	15,411.4	-0.81
St_Hanshaugen	55,866.6***	7,448.0	7.50
Stovner	-62,038.8***	7,588.1	-8.18
Søndre_Nordstrand	-64,009.4***	7,396.1	-8.65
Ullern	26,674.3***	8,655.0	3.08
Vestre_Aker	9,212.2	8,780.4	1.05
_cons	-26,111,437.8***	1,228,443.5	-21.26
F statistic	5,441.93		
R-squared	0.88		
N	27,032		

* *p*<0.1; ** *p*<0.05; *** *p*<0.01 Robust standard errors are the Huber/White-estimators of variance

Dxxxk_1: Salesprice ≤ 3 000 000 kr **Dxxxk_2:** 3 000 000 kr < Salesprice ≤ 5 000 000 kr **Dxxxk_3:** 5 000 000 kr < Salesprice

Table 9: Charm and Round Numbers Listing Price Regression Results for Group 2: 3 000 000 kr < Salesprice ≤ 5 000 000 kr

Dep. Var: Salesprice	Coefficient	Robust Standard Error	t
CD50k_2	30,432.8***	10,828.9	2.81
CD90k_2	-3,341.6	10,791.4	-0.31
CD490k_2	-5,259.2	13,401.5	-0.39
CD900k_2	84,182.2***	14,820.4	5.68
CD990k_2	-1,714.3	12,313.5	-0.14
D100k_2	55,890.3***	11,037.6	5.06
D500k_2	50,948.3***	15,290.9	3.33
Dmill_2	86,572.1***	17,717.0	4.89
Value_Evaluation	0.7***	0.0	99.54
Livingarea	1,026.1***	158.3	6.48
Build_Year	-14.6	72.2	-0.20
Actual_Sale_Year	11,755.0***	1,289.9	9.11
Actual_Sale_Month	-5,241.3***	710.1	-7.38
Apartment	-70,866.3***	14,387.0	-4.93
RowHouse	-4,671.8	12,634.6	-0.37
SemiDetached	-2,029.5	14,547.2	-0.14
Alna	-112,815.7***	19,709.0	-5.72
Bjerke	-12,272.9	16,460.1	-0.75
Frogner	-26,212.7*	15,589.8	-1.68
Gamle_Oslo	-38,333.6**	16,220.0	-2.36
Grorud	-126,399.2***	19,475.5	-6.49
Grünerløkka	-52,219.7***	16,294.7	-3.20
Nordre_Aker	67,354.8***	15,535.6	4.34
Nordstrand	-47,031.6***	15,777.7	-2.98
Sagene	-13,674.8	16,085.1	-0.85
Sentrum	-152,140.2**	65,770.2	-2.31
St_Hanshaugen	-17,883.0	15,234.7	-1.17
Stovner	-151,738.3***	17,579.8	-8.63
Søndre_Nordstrand	-212,811.5***	16,430.1	-12.95
Ullern	-33,871.9**	14,991.5	-2.26
Vestre_Aker	-33,646.2**	14,676.2	-2.29
_cons	-22,461,890.7***	2,622,615.4	-8.56
F statistic	834.34		
R-squared	0.75		
N	15,740		

* p<0.1; ** p<0.05; *** p<0.01 Robust standard errors are the Huber/White-estimators of variance

Dxxxk_1: Salesprice ≤ 3 000 000 kr **Dxxxk_2:** 3 000 000 kr < Salesprice ≤ 5 000 000 kr **Dxxxk_3:** 5 000 000 kr < Salesprice

Table 10: Charm and Round Numbers Listing Price Regression Results for Group 3: 5 000 000 kr < Salesprice

Dep. Var: Salesprice	Coefficient	Robust Standard Error	t
CD50k_3	5,619.9	37,380.6	0.15
CD90k_3	-774.1	38,162.5	-0.02
CD490k_3	-84,208.8*	43,471.8	-1.94
CD900k_3	-9,735.4	46,367.3	-0.21
CD990k_3	-49,089.7	42,676.7	-1.15
D100k_3	142,967.4***	36,902.0	3.87
D500k_3	187,663.3***	42,597.0	4.41
Dmill_3	304,493.9***	54,500.8	5.59
Value_Evaluation	0.8***	0.0	81.48
Livingarea	422.5	378.1	1.12
Build_Year	-125.3	220.7	-0.57
Actual_Sale_Year	15,949.1***	4,772.4	3.34
Actual_Sale_Month	-19,720.4***	2,284.7	-8.63
Apartment	-246,291.7***	29,882.6	-8.24
RowHouse	-114,368.6***	24,346.0	-4.70
SemiDetached	-32,586.5	25,725.2	-1.27
Alna	-170,261.9**	66,171.2	-2.57
Bjerke	-46,526.9	43,238.3	-1.08
Frogner	107,518.6**	44,919.3	2.39
Gamle_Oslo	149,465.3***	55,865.1	2.68
Grorud	-187,180.5**	86,742.2	-2.16
Grünerløkka	202,116.3**	79,413.6	2.55
Nordre_Aker	235,503.3***	37,524.3	6.28
Nordstrand	-30,961.4	36,184.4	-0.86
Sagene	227,082.1***	56,003.6	4.05
Sentrum	82,856.6	211,452.0	0.39
St_Hanshaugen	149,503.8***	49,403.6	3.03
Stovner	-261,023.6***	58,104.6	-4.49
Søndre_Nordstrand	-332,880.2***	50,822.1	-6.55
Ullern	47,030.0	39,697.7	1.18
Vestre_Aker	-11,190.2	37,206.7	-0.30
_cons	-30,528,552.6***	9,678,285.1	-3.15
F statistic	930.44		
R-squared	0.91		
N	9,086		

* *p*<0.1; ** *p*<0.05; *** *p*<0.01 Robust standard errors are the Huber/White-estimators of variance

Dxxxk_1: Salesprice ≤ 3 000 000 kr **Dxxxk_2:** 3 000 000 kr < Salesprice ≤ 5 000 000 kr **Dxxxk_3:** 5 000 000 kr < Salesprice

The results of the regressions are quite remarkable, as only the CD900k charm listing price dummy in price group 2, and the CD50k for price group 1 and 2 is statistically significant at conventional levels. At a 10% significance level we find that CD900k in group 1 and CD490k in group 3 are significant, although the latter in fact has a negative(!) coefficient. This is a quite stark indication that the hypothesis of charm listing prices having a positive effect on the final sales prices, should be rejected in most cases. None of the above results change when the standard errors are re-calculated using the HC3 heteroskedasticity-correction, providing some additional robustness to the results.

The round numbers listing prices that were included as a check, actually turn out positive coefficients that are statistically significant at the 1% level, across all the 3 price groups. This is the exact opposite of what Allen and Dare (2004) find in their data for the American market. Also, the absolute values of the estimated coefficients for the round number dummies increase dramatically from group 1, via group 2, to group 3. On average, the estimated effect of using one of the three round number listing price designs in price group 3 is at least 4-5 times larger than in group 1. It thus seems as the effects are relative to the price level of the dwelling in question, and that the effect is increasing in the level of the dwellings market worth.

As mentioned earlier, the 50k dummy can be interpreted in multiple ways. Some may not agree that 50 000kr should be interpreted as a charm price. To some extent I agree with this view. Firstly, in the low price segment it is not uncommon for value evaluations to end with 50 000kr. Actually, in 57% of the instances where the asking price ends in 50 000kr, the asking price is also identical to the value evaluation. That means that only 43% of the time the 50k charm dummy is plausibly interpreted as a charm price. Thus, the finding that the 50k charm dummy has a positive and significant effect on the final sales price in price group 1 and 2, cannot solely be attributed to its function as a charm price.

Another notable finding is that the coefficient of the charm price CD900k_2 is not statistically significantly different from the coefficient of Dmill_2. Therefore, if we assume that the choice is between setting an asking price either at the million marker or at a 900k marker, then the effect on final sale price is indistinguishable betwen the two options.

Two issues needs to be addressed; firstly Allen and Dare (2004) include data on the different real estate agencies, which are involved in the transactions. They follow the Heckman two-step procedure to control for the potential effect of self-selection. The reason for this is that the broker may have knowledge of which dwelling is more likely to experience a positive effect of a charm asking price than others, and thus the dwellings we observe in the sample that use a charm asking price, are the ones more likely to have a positive effect. As I do not have any data on the real estate agencies involved in the transactions, a correction for this cannot be undertaken. However, if anything, the coefficients on the charm listing price dummies should then be biased upwards. As for the most part they are found to be not statistically significant, this selectivity effect is not likely to drive the results.

One could also suggest that, there is a possibility that some of the sellers (or their real estate agents) know that it is the round numbers listing price strategy that pays off in the market. If that is the case, then a correction for this selection bias should be conducted as the estimated coefficients then would be inflated upwards for the round number listing prices. Alas, since data on this is not available this procedure cannot be done for this sample.

The second issue with the specification is the lack of a measure that captures the effect of a prolonged marketing time on sales price. This requires an estimation of a proportional hazard rate model (usually Weibull or Cox type of specification), as the time on market is simultaneously determined along with the sales price. The dataset which is being used in this analysis only contains observations of actual transaction and not those that withdrew from the market. Any model estimating time on market would need to take account of this censoring. The results from an attempt to construct such a model shows that the property characteristics can only explain 4% of the variation in the time on market durations. To use the predictions of such a model to control for the expected time on market in the charm regressions is likely to induce a lot of noise, and is thus not included.

However, a different regression specification is constructed in order to check the robustness of the charm listing price regressions. It might be plausible that the effect on final sales price from the chosen listing price design is related to the degree of "underpricing", as measured by the difference of asking price from value-evaluation. Therefore I construct a specification in which I include a dummy equal to 1 if asking price = value evaluation ("askonval"). This will in most cases pick up the same effect as the round number dummies did in the previous specification, as value evaluations tend to be on round numbers.

Dummies are also constructed for the most common listing price designs, found in Table 5, which all have a listing price lower than the value evaluation. For most transactions this will pick up a similar effect to that of the charm listing price dummies, found in Tables 8 through 10. These "underpricing" dummies are included in a separate regression specification, as we do not want to include both these and the "askonval" because what we are effectively comparing against is then the handful of remaining observations that do not have either charm pricing or round number pricing. This is thus another check to see if what we found in Tables 8 through 10 was driven by the chosen specification, which compares the round number pricing and charm pricing against (the minority) of all other pricing strategies. Separating the two specifications allows us to more directly compare the effect of round number pricing versus charm pricing.

Tables 11 and 12 display the results from the two following regression specifications, which are estimated for the 3 different price groups separately:

$$\text{Salesprice} = \boldsymbol{\beta}(\text{Askonval, Value Evaluation, Dwelling's Physical Characteristics, Time Trend, City Borough Dummies}) \qquad \textbf{(3)}$$

This specification is designed to pick up the effect of no under-pricing, i.e. asking price equals value evaluation.

The opposing regression is designed to specifically pick up the effect of “under-pricing”, i.e. asking price is below value evaluation:

$$\text{Salesprice} = \boldsymbol{\beta}(\text{Most Common Under-Pricing Dummies , Value Evaluation, Dwelling's Physical Characteristics, Time Trend, City Borough Dummies}) \quad \textbf{(4)}$$

I follow Allen and Dare (2004) and use standard errors calculated with the HC3. As shown by MacKinnon (2012) it is a good correction for heteroskedasticity, most notably in small samples. The present sample size is quite large, so it should not make a world of a difference. However, the idea is that it at least will be a stricter measure, and leads to rejections more often since the test statistic has much thicker tails than the standard normal distribution.

Table 11: No-Underpricing Regression Group 1-3

Sales Price	Coefficient	HC3 Standard Error	t	n
Askonval_1	57,445.3***	2,131.8	26.95	27,032
Askonval_2	105,923.6***	4,569.2	23.18	15,740
Askonval_3	344,190.5***	14,799.4	23.26	9,086

* *p*<0.1; ** *p*<0.05; *** *p*<0.01

Table 12: Underpricing Regression Group 1-3

Sales Price	Coefficient	HC3 Standard Error	t
underP10k_1	24,436.2***	2,958.7	8.26
underP50k_1	-13,356.5***	4,305.4	-3.10
underP60k_1	660.6	3,295.4	0.20
underP100k_1	-62,274.6***	6,439.2	-9.67
underP110k_1	-16,698.9***	3,870.6	-4.31
underP150k_1	-105,844.1***	8,785.8	-12.05
underP200k_1	-164,422.1***	14,238.5	-11.55
underP210k_1	-111,044.9***	8,014.7	-13.86
underP10k_2	32,981.0***	6,660.8	4.95
underP50k_2	13,959.1	9,954.4	1.40
underP60k_2	3,436.7	9,776.6	0.35
underP100k_2	-16,107.7	14,267.0	-1.13
underP110k_2	-20,804.4***	6,823.5	-3.05
underP150k_2	-53,197.6***	13,843.4	-3.84
underP200k_2	-121,359.7***	18,566.4	-6.54
underP210k_2	-87,025.2***	10,391.5	-8.37
underP10k_3	65,209.4***	21,783.8	2.99
underP50k_3	42,738.3	28,823.9	1.48
underP60k_3	46,110.4	89,426.8	0.52
underP100k_3	62,282.9	40,290.0	1.55
underP110k_3	-21,579.1	21,336.2	-1.01
underP150k_3	-102,468.4***	36,171.9	-2.83
underP200k_3	22.3	60,556.4	0.00
underP210k_3	-11,722.8	28,592.9	-0.41

* *p*<0.1; ** *p*<0.05; *** *p*<0.01

Only coefficients of the variables of interest are included, control variables are omitted for brevity. Summary Statistics for Group 1, 2 & 3 are represented in Table 13.

Table 13: Summary Statistics for Underpricing and No-Underpricing Regressions

		Underpricing regression	Askonval regression
Group 1	F statistic	5,453.31	7,193.31
	R-squared	0.88	0.88
	Number of Observations	27,032	27,032
Group 2	F statistic	808.59	1,135.58
	R-squared	0.75	0.76
	Number of Observations	15,740	15,740
Group 3	F statistic	909.91	1,205.15
	R-squared	0.91	0.92
	Number of Observations	9,086	9,086

The results clearly indicate that those dwellings were the asking price is equal to value evaluation sell for more, on average, across all the three different market segments. As an example, take the coefficient of Askonval_1 in table 11. This dummy variable indicates that the dwelling had an asking price equal to value evaluation. Its coefficient is 57 455 kr, indicating that it is predicted to sell for more than an object with the same value evaluation that was priced *below* value valuation. Similarly in Table 12 we find that the dummies for underpricing are mostly negative, where the reference category in that specification is the dwellings were asking price was equal to value evaluation.

The specifications controls for value evaluation as a measure of the dwellings quality, thus the "askonval" and underpricing dummies should pick up the extra effect, not the variations in value evaluations and dwelling-quality as such. Again, we see estimated coefficients that are in a similar range to those found for the round numbers listing prices in table 8-10. And furthermore, it seems like the premium for setting an asking price equal to value evaluation is increasing as we move from a low price segment to the highest priced market segment.

The underpricing regression results further backs up the finding that a charm listing price strategy does not pay off in the marketplace. We find mostly that the estimated coefficients are strongly statistically significant and negative. The exception here is the strategy of underpricing by 10 000kr, which is estimated to have a positive effect on final sales price that varies in the range of 24 436 kr to 65 209 kr, for the lowest price and the highest price segment respectively. The standard errors for the estimated coefficients are increasing from group 1 through 3, so any confidence interval of the point effect would be increasingly wide for the different market segments.

It can be pointed out that the estimated negative effects of underpricing, are always smaller than the magnitude of underpricing itself. For instance, the underpricing of 150 000kr below value evaluation always has a coefficient which is of a lesser magnitude than 150 000kr, thus even though the underpricing is strong, the effect on final sales price is smaller than the initial underpricing. Also, the effect of underpricing does not follow the same pattern we found in the round numbers listing price-effect, which was increasing as we moved from the low price market segment, to the high price market segment.

When constructing a continuous variable for underpricing, which is simply the difference of asking price-value to evaluation, and rerunning the regression for the three different market segments, we find that the effect of underpricing varies from .81 to .93, and is significant at the 1% level. Meaning that, again the underpricing has a negative estimated effect on the final sales price. Per krone of underpricing ,the estimated coefficient on final sales price is a reduction of 81 to 93 cents (øre). Under a causal interpretation this would imply that it is not only the most common underpricing strategies that have a negative effect on final sales price, but possibly all of the underpricing strategies more in general.

To summarize the main findings;

The results point in the direction of a positive effect of a round number listing price design, where in most cases the asking price is set equal to the value evaluation. The effects of a charm listing price design are for the most part not statistically significant across the three different market segments, although some exceptions are found. The effect of underpricing is estimated to have a (strong) negative effect on the final sales price.

The reason as to why so many make use of a charm listing price design and underpricing if it does not have any positive impact on the final sales price, is not clear at this point. Part of the effect we have found might be due to unobservable characteristics, although using the value evaluation as a control for this largely eliminates that sort of error. It is possible, although purely speculation at this point, that people hold false beliefs and think that the charm listing price design will attract more buyers and thus are likely to bid up prices. Perhaps it is also a reflection of the fact that real estate agents have incentives to sell dwellings faster than what might be optimal for the owner, thus wanting to set a lower asking price to increase the possibility of a match in the market (Levitt & Syverson, 2008). There could be a number of reasons for the observed effects of the listing price design, and both rational and behavioral interpretations are likely to contribute with further knowledge on this particular issue.

3.3 Sales Price: Clustering at Round Numbers

An interesting aspect of the distributions of prices in the housing market reveals that there is a considerable amount of clustering in the sample. This means that there is an unusual high amount of dwellings being transacted at certain price points, more than what we would expect if prices were drawn at random from a smooth probability distribution. The best way to represent this is by a graphical analysis, where the distributions of prices are displayed in histograms. To be able to detect the effects of round number pricing and charm pricing, all prices are rounded down to be placed in a 10 000kr bin. In this way, the 3 million kr bin contains all prices from 3 000 000 to 3 009 999, and so on and so forth.

As shown in 1.3.1, the value evaluations have a strong tendency to cluster at round numbers; prices ending with 50 000's, 100 000's and million markers have a much higher transaction count than other prices. However, from 1.3.2 it is clear that, when we look at asking prices the tendency of the distribution is to cluster at charm-prices ending with 90 000kr. That is, 10 000kr below any hundred thousand or million marker.

Both of those prices are indicators of a dwellings market value, and carry significant information to the potential buyer, but ultimately it is the final transaction price that really matters. So how will the two opposing forces of round numbers bias and charm pricing, affect the final market outcome?

A measure of the excess mass at round numbers is represented by the spikes in the distribution of sales prices found in Figure 11. The histogram gives us an indicator of the overall distribution of the data, although it is difficult to see exactly which price points are responsible for the spikes.

When we take a closer look in Figure 11, at the range of sales price between 2 and 3 million kr, we can clearly see that it is the round numbers that are responsible for the spikes. Figure 12 shows that those price points are transacted far more often than the surrounding prices. If we assume a random draw from a smooth probability distribution as a benchmark for the underlying distribution of prices, we see that no choice of such a distribution can explain the systematic occurrence of high transaction counts at round numbers.

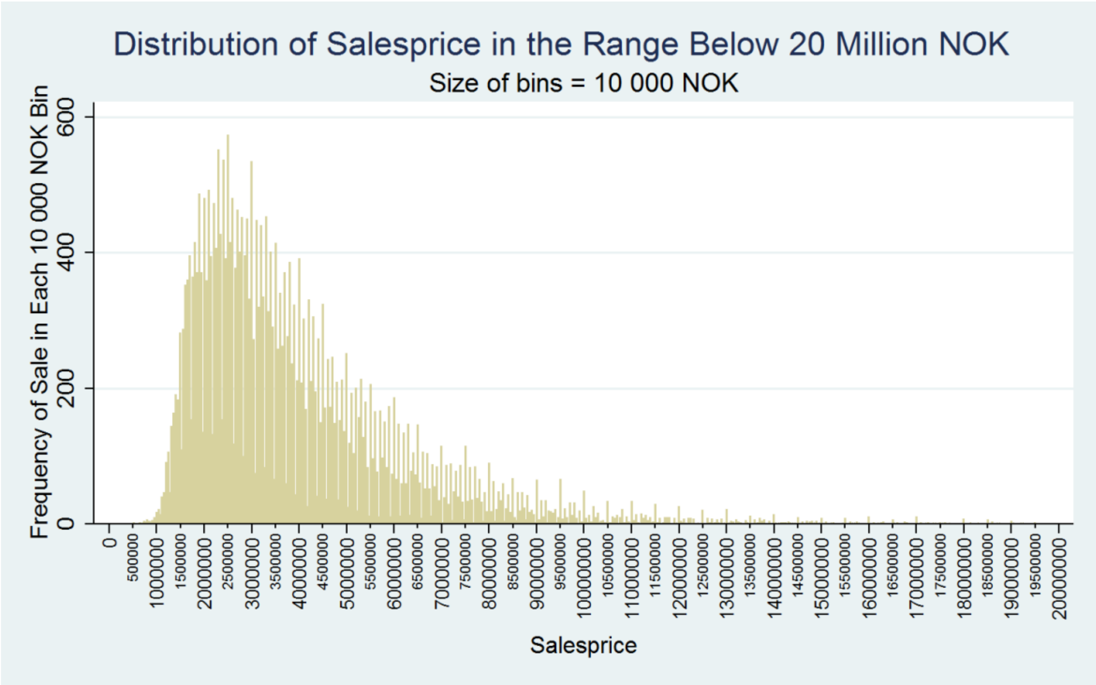

Figure 11 - Distribution of Sales Prices

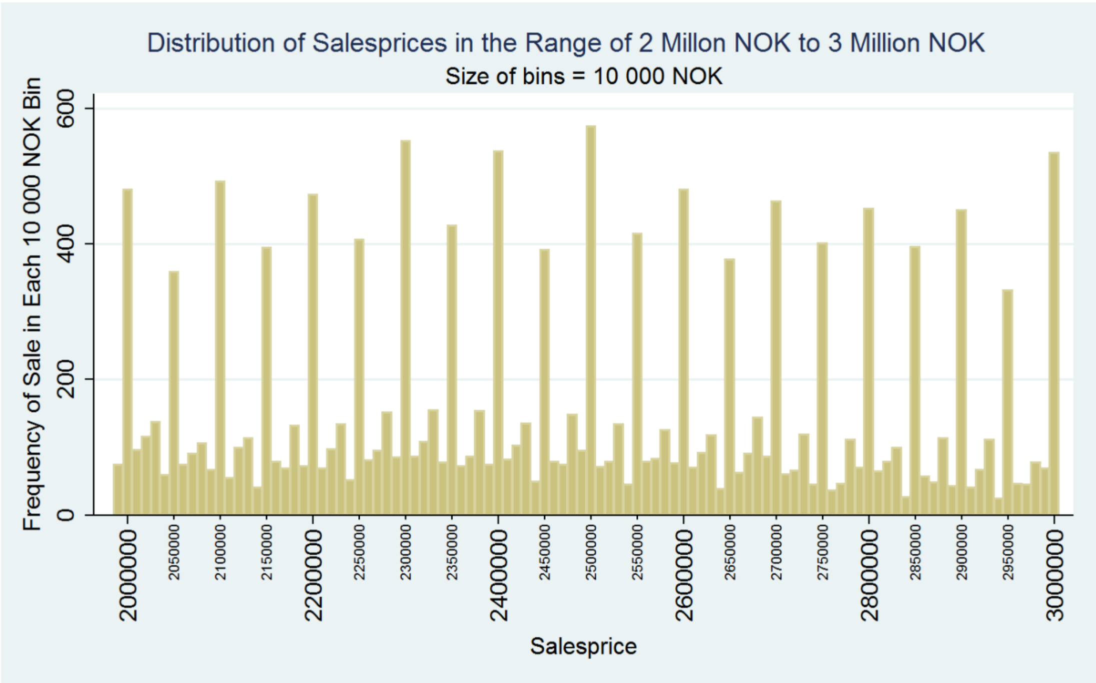

Figure 12 - Sales Prices Clustering at Round Numbers

Over the course of the 8 years for which we have data, the percentage of dwellings that sold for more than their asking price was 63%. This reflects the fact that it has been a seller's market, where demand for housing is large. However, 29% of dwellings ended up with a sales price below asking price.

The frequency of dwellings which had sales price equal to asking price was 8%. And the dwellings that ended up with a final sales price equal to the value evaluation made up 8,5% of the sample. This might indicate that the relative strength of the two price anchors; asking prices as charm pricing and value evaluations as round numbers, are possibly quite similar in the magnitude in which they affect the final transaction price.

We should also note that the distribution of sales prices is more evenly distributed, when compared to those of asking prices and value evaluations, as there is more mass in the bins surrounding the round numbers and the charm-prices. Thus, it seems as if the market partly corrects for some of the round numbers bias evident from value evaluations, and some of the charm pricing bias from asking prices. The final sales price distribution is thus a bit smoother than the distribution of value evaluations and asking prices.

Still, the remaining clustering of sales prices at round numbers cannot readily be explained by a story where value evaluations are round numbers biased and buyers simply pay the value evaluation. Nor does the data fit a description in which the buyers simply pay the asking price stated by the seller. Therefore, we will now look further in to how the negotiation process itself can be an explanatory factor for the observed clustering.

The following analysis will rely on the empirical approach found in Pope et al. (2014), from here on referred to as (PPS).

3.3.1 Round Numbers Regression Analysis

In order to quantify the effects of round numbers, and test for statistical significance I follow PPS' outline for a regression design. Firstly, the sample is now restricted to those dwellings whose final sales price lands exactly on a price which is cleanly divisible with 5 000kr. This amounts to 99,6% of the dwellings in the total sample, and allows for calculation of positive sales volumes for each of those discrete price points. Furthermore, I also restrict the sample to dwellings whose final sales price was above 1 075 000kr and below 10 100 001kr, in an attempt to eliminate the effect of outliers. This also simplifies the estimation of the 7th-degree polynomial in sales price, which is constructed to account for a smooth underlying distribution of the sales count found in each 5 000kr price bin. This leaves us with 50 655 out of the 51 858 observations in the initial dataset (98% of the sample).

I adopt PPS' notation (Pope et al., 2014) and the following regression specification is run:

$$Q_j = \theta F^7(p_j) + \beta_1 X_j^{50k} + \beta_2 X_j^{100k} + \beta_2 X_j^{500k} + \beta_3 X_j^{mill} + \varepsilon_j \qquad (5)$$

The dependent variable Q_j denotes the total number of sales observed at the j^{th} price point, as measured in 5 000kr increments. So that Q_{1000} is the price point of 5 000 000kr. The first term in equation (5) is a 7^{th}-order fractional polynomial of sales price which captures the overall distribution of sales volumes. More details on the estimation of this polynomial is found in Appendix D. The idea is that this kind of smoothing can account for the underlying distribution of sales counts across the various ranges of sales prices. In Figure 13 we see the result of the fractional polynomial plotted against the actual observed transaction count.

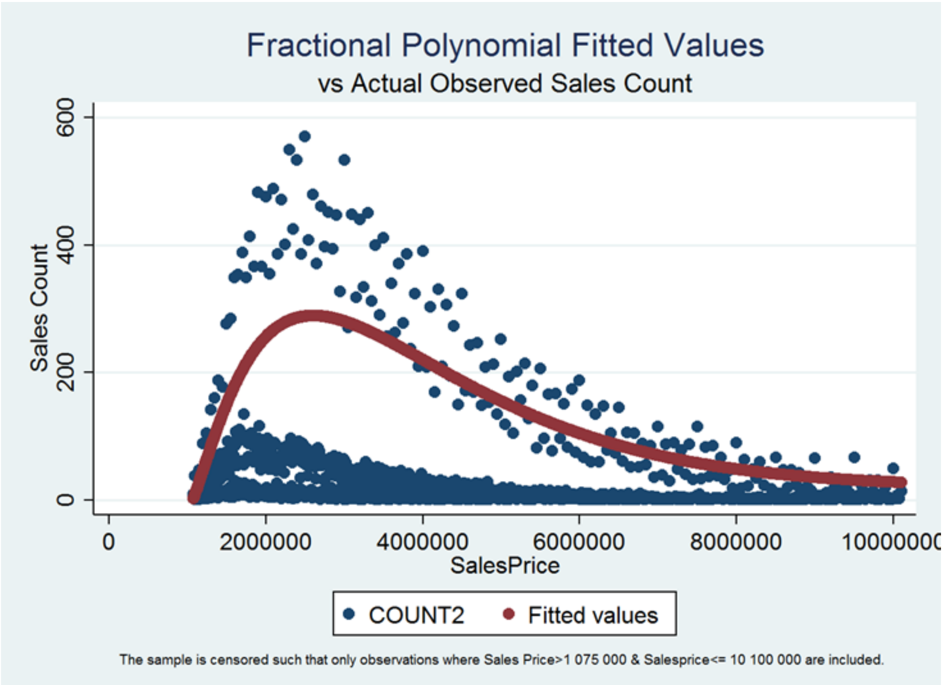

Figure 13 – Fractional Polynomial of Salesprice Which Smoothes the Sales Count Distribution

The four X_j terms are indicator variables for prices divisible exactly by 50 000kr 100 000kr, 500 000kr and 1 million kr:

- The 50k dummy is equal to 1 for any sales price ending exactly on any 50 000kr marker: 50 000, 100 000, 150 000 → 10 000 000

- The 100k dummy is equal to 1 for any sales price ending exactly on any 100 000kr marker: 100 000, 200 000, →10 000 000

- The 500k dummy is equal to 1 for any sales price ending exactly with: 500 000, 1 million, → 10 million

- The “mill” dummy is equal to one for any price ending exactly on any million price point: 1 million, 2 million, → 10 million

These indicators are now *additive* in such a way that a price of 3 000 000kr will have a value of 1 for each of the four indicator terms, as it is cleanly divisible by each of those round numbers. A price of 9 500 000 will have indicators equal to 1 only for $X_j^{50k},\ X_j^{100k}\ and\ X_j^{500k}$. A price of 5 300 000 will only have an indicator equal to 1 for the $X_j^{50k}\ and\ X_j^{100k}$ variables. A price of 1 850 000 will only have an indicator equal to 1 for the X_j^{50k} variable. Thus, it should be clear that the interpretation of the dummies are different to those found in the regressions of section 3.2.2, as those were *mutually exclusive* dummies, and the specification just described in this section have additive dummies.

Therefore, the estimated regression coefficient β_1 is the extra sales volume found at 50 000kr thresholds, relative to other 5 000kr price points. In similar fashion the marginal effect on sales volumes at 100k price points is given by $\beta_1 + \beta_2$. The 500k- and million kr thresholds are given by $\beta_1 + \beta_2 + \beta_3$ and $\beta_1 + \beta_2 + \beta_3 + \beta_4$, respectively.

Table 14 - Round Numbers Effect on Sales Count

Number of Sales	Coefficients	
	(I)	(II)
SD50k	246.747*** (0.616)	248.56*** (0.62)
SD100k	85.252*** (0.638)	81.12*** (0.65)
SD500k	31.291*** (1.211)	31.50*** (1.20)
SDmill	14.143*** (1.604)	13.72*** (1.59)
Above SDmill		-27.74*** (1.23)
Below SDmill		-18.95*** (1.20)
Seventh order polynomial in sales price	Yes	Yes
F statistic	42,590.89	40,609.49
Adj. R-squared	0.90	0.91
N	50,655	50,655
Number of 5 000 kr price bins in estimation	1477	1236
Mean sales count at other non-focal (5k) price poins	51	51

* *p*<0.1; ** *p*<0.05; *** *p*<0.01 Standard errors in parenthesis

To get a sense of how large the effects of the round number focal points are, it is useful to note that the mean sales count at non-focal prices was 51 sales.

From specification I we can tell that the lowest of the round number focal point dummies, where prices are divisible by 50 000kr, has a sales volume almost 5 times larger than other 5 000kr price points. Pope, Pope and Sydnor (2014) suggest that their lowest round number focal point dummy ($5k) represent both some degree of convenience rounding and the effect of the focal point. It is reasonable to believe that the 50 000kr divisible prices reflect the same two factors in the Norwegian market. There is another 85 extra sales estimated to be in each of the 100 000kr divisible focal points, and the half million and million round numbers also contribute to a greater sales volume than those prices which are exempt a focal point. The additional effect of those two focal points was 31 and 14 added sales, respectively.

So even if we allow for some degree of convenience rounding, essentially hypothesizing that market participants are using a pricing grid that mostly consist of 50 000kr intervals, we still observe that the focal points of 100k, 500k and million markers attract a substantial mass of excess sales.

We can summarize the results using the 50k focal point as a benchmark. The effects we find are that 100k focal points have a sales count which are more than 29% larger than other 50k price points ($\frac{51+246+84}{51+246}$). The 500k focal points have a 39% larger sales volume than other 50k focal points, and the million marker focal points attract a mass of sales which is 44% larger relative to other 50k focal points. Although the findings here are not directly comparable to those in PPS' analysis, due to currency conversion and choice of focal points, the relative increase in sales found in the Oslo data do seem to be similar to those found in the American market. PPS report an increase in sales count for $25k divisible focal prices that are 24% higher and a 44% increase for $50k divisible focal points, both compared to other $5k divisible price points.

In regression specification II of Table 14, I have added indicators for dwellings where the sales price is 20 000kr to 70 000kr ***above*** a million-kr focal point. E.g. dwellings with a sales price in the range of 4 020 000 to 4 070 000kr have the indicator "Above SDmill" equal to 1. In similar fashion I construct an indicator variable; "Below SDmill" for those dwellings with sales prices 20 000kr to 70 000kr ***below*** a million-kr focal point. The reason for designing the dummies in such a way, is to avoid picking up the effect of charm asking prices, in those cases where buyers simply pay the asking price. As shown earlier in section 2.2, the occurrence of charm pricing was approx. 65% of all transactions, and 8% had sales price equal to asking price, thus roughly 5% of the sample simply paid the charm asking price.

From column II, also in Table 14, we see that the coefficients on the focal points are similar to those found in column I, and all coefficients are significant at the 1% level. We see that both the "Above

SDmill" and "Below SDmill" are negative, reflecting that the million-kr focal point attracts mass from both sides. It indicates that some dwellings which have a market worth just *above* a million-kr focal point, are actually instead being sold at the very salient focal point, thus selling for *less* than it would if the focal point was absent. Similarly, it suggests that some dwellings which have a market worth just *below* a million-kr focal point, are actually ending up selling at the focal point instead. In this case it is thus selling for *more* than it would if the focal point was absent.

We can thus say that the million-kr focal point pulls sales mass both from above and below, and we note that the pull is stronger from above than from below, with a ratio of (Above/Below) = 1,46. I follow PPS and interpret a ratio above unity as reflecting that more mass of sales is being pulled from the seller's side. A ratio below unity indicates the opposite, namely that more mass of sales is being pulled from the buyer's side of the price distribution.

3.3.2 Heterogeneity Over Time

As the housing market tend to be cyclical, and there are variations in price growth across the years covered in the data, I would like to assess if there is any substantial heterogeneity in the effect of focal points across time.

Figure 13 displays the estimated ratio of sales volumes for the million-kr focal price compared to; all the 5k price bins contained in the sample and the 50k-, 100k- & 500k-focal prices. The estimated ratios are from a regression identical to that found in Table 14, column I, which now is conducted for each year in the sample separately. Full regression results are omitted for the sake of brevity.

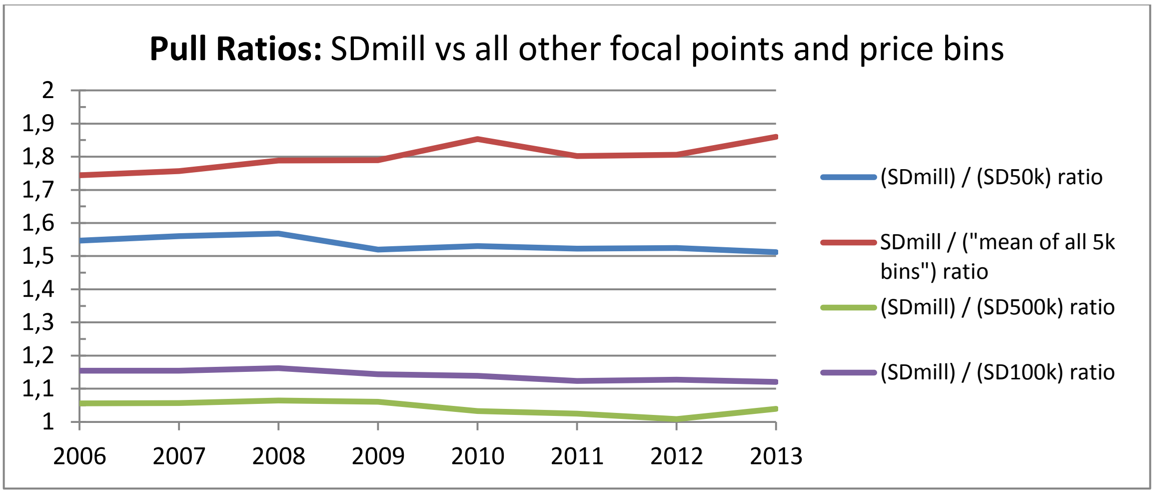

Figure 14 – Estimated Million-kr Focal Price Pull of Mass Ratios

We see that compared to the mean sales count of all prices found in the data sample, the effect of the million-kr focal point has been increasing over time.

However, when compared to the other focal prices in the sample, the effect of the million-kr focal price has marginally decreased. The flat or even marginally decreasing effect of the million-kr focal point is different to the findings of PPS, where they estimate that the $50k focal price to $5k focal price-ratio is increasing over the years of 1998 to 2008, and peaks at a ratio of 2 in 2007. In the Oslo data the effect of the million-kr focal point compared to the effect of the 500k focal point was at parity in 2012. However, the relative stable ratios which are consistently above 1 suggest that the million-kr focal point in general has a stronger effect on sales than any other focal point.

3.3.3 Pull of Mass from Seller or Buyer?

In the regression specification of Table 14, column II we found that there was an asymmetry in the effect of the million-kr focal point, as it pulled more mass from above than below. To see if there is any variation in the effect of pull of mass over time, a regression specification identical to the one found in Table 14- column II, is conducted for every year in the period 2006-2013. Full regression results are again omitted for brevity.

The regression coefficients for "Above SDmill" and "Below SDmill" are used to calculate the ratio of pull of mass at the million-kr focal points. As the Oslo housing market both experienced rapid price growth, a small downturn and then accelerating growth again in this period of time, it should be useful to see if the effect of the focal points varies across time. In Figure 14 we see the ratio of the sales count pulled from 20 000kr to 70 000kr above versus below a million-kr focal point, plotted out across the years 2006-2013.

All the regression coefficients for both the "above"- and "below"-indicators were negative, reflecting that the million-kr focal points attract excess mass from the surrounding price points for all years included in the sample. The pull of mass is consistently higher from above the million-kr focal points, than it is from below. Thus, the ratio of the two is always greater than unity for the entire sample.

As Figure 15 shows, the pull ratio is for the most part stable in an interval between 1,4 to 1,7, however we see a notable peak in 2012, and low points in 2006 and 2013.

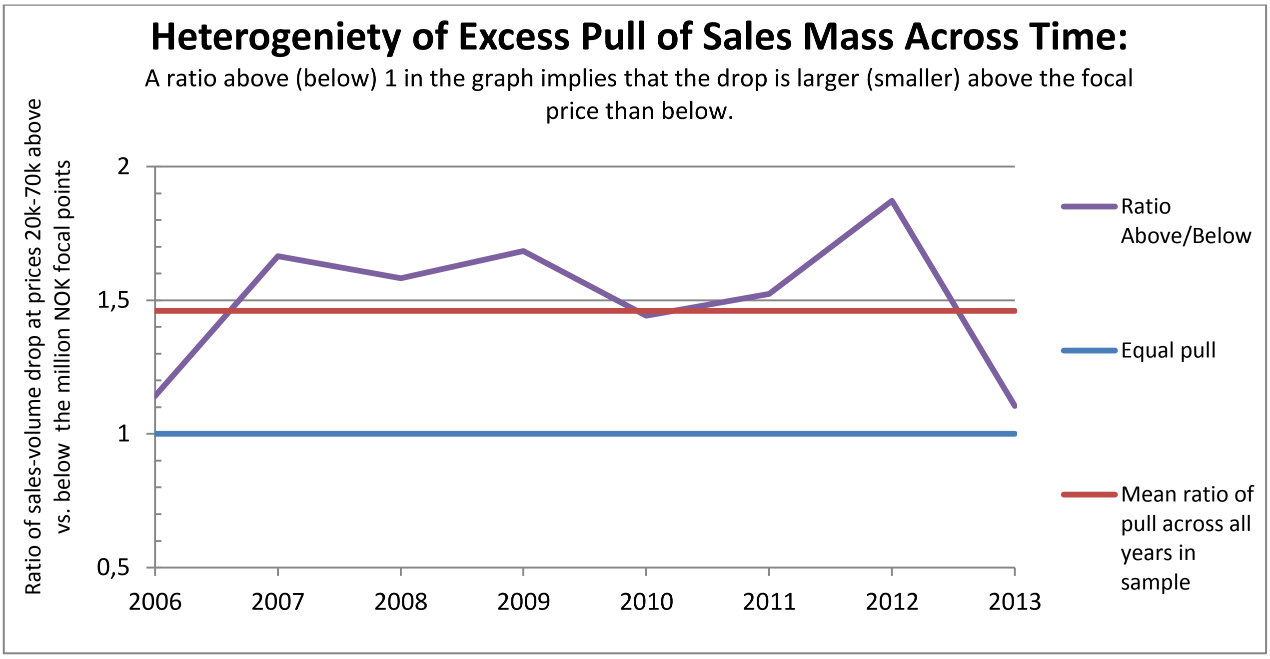

Figure 15 – Heterogeneity of Mass of Sales Above/Below Million-kr Focal Points Across Time

The mean ratio across all the years in the sample is 1,46, implying that the million-kr focal point on average pulls 46% more mass of sales from the seller's side of the price distribution. Of course, we can only speculate as to why sellers are potentially accepting a lower sales price than what would have been if the focal point was absent. Pope et al. (2014) offer a potential explanation, which is that sellers already believe they are getting a good return on the dwelling, and are accepting because of considerations of fairness or other social norms. Thus, applying insights from the theory of fairness by Fehr and Schmidt (1999) in the housing market could be a future research agenda, see Schein (2002) for an apt example of this.

Perhaps surprisingly we do not find, as PPS does, that the ratio falls below 1 during the financial crisis year of 2008. The Norwegian house price index fell from Q1 2007 to Q3 2009, but this is not reflected in the pull of mass ratio. However, as the house price index again fell from Q1 2013 to Q3 2013 we see that this is accompanied by a sharp drop in the ratio of mass pulled from the sellers side. The direction of the shifts in pull of mass seems to be a conundrum, as standard economic theory would suggest that sellers are pressed in a downturn market, and thus accept lower price. On the contrary, the ratio of pull of mass above/below the million kr threshold seems to decrease when sales prices are decreasing. In that regard, it points towards more mass being pulled from the buyer's side in a downturn market. Even though this seems to be an interesting aspect to investigate further, we must keep in mind that the short data sample only allows us to find correlations and not causation. In fact, it might be a spurious link altogether. In the absence of a longer and richer data set, we can only speculate as to what the specific mechanism driving the pull of mass ratio is.

4 Conclusion and Remarks

From the literature overview in the first section, we have seen that the occurrence of behavioral biases is well documented in the literature. As an example, loss aversion has empirically been found to affect real estate markets in different parts of the world, and is also demonstrated in many experimental settings. This indicates robustness of the phenomenon across dimensions of time and space. The economic effects are substantial and do not vanish when exposed to market forces, or when agents are more experienced.

Price expectations are a key component to the housing market, and are empirically difficult to assess. Expectations can potentially drive markets away from “fundamentals”, especially if market participants are prone to herding behavior. The user cost of housing framework adopts an asset-market approach to the housing market, however, using this model as a baseline to assess house prices might be problematic as heterogeneity, and limits to arbitrage are key institutional features of housing markets. In a low interest rate environment, the price expectations can dominate in the calculations of the user cost yielding negative prices, and the theory becomes undefined. An alternative approach was analyzed (N. Barberis et al., 1998), where the housing market is described in relation to investor sentiment, allowing for both overreactions and underreactions to the events occurring in the marketplace. Indications of sentiment in both the U.S. and Norwegian housing markets were offered.

The possible behavioral influence of prices on market participants is at the heart of this thesis. The effects of different asking price strategies, as found in the literature, are multi-faceted and pull in opposite directions. Some reports find that round numbers listing price have a positive effect on final sales price (Palmon et al., 2004), while others indicate that charm asking prices translates into higher final sales prices (Allen & Dare, 2004).

In the empirical part of this thesis, I have exploited the rich nature of the dataset and analyzed the interlinkages between value evaluation, asking price and final sales prices. I find that:

- Value evaluations are good predictors of final sales price, but on average they tend to be lower than final sales price. Some characteristics of the dwellings are not sufficiently incorporated into the estimates of market worth. The surveyors cluster their value evaluations at round numbers.

- Asking prices cluster at charm prices, that is “just-below” a round number. As a whole, I find very few indications that a charm listing price design has a positive impact on final sales prices. However, a round number listing price design does have a positive effect on the final sales price, and the magnitude is increasing as we move from the low price segment to the high price segment of the market. As a check of this (surprising) result, I show that dwellings which have an asking price equal to value evaluation, consistently obtain a higher final sales price than other listing price strategies. The dwellings that are “under-priced” (having an asking price which is lower than the value evaluation), sell for comparatively less. These findings are consistent across all the three market segments.

- Final sales prices cluster at round numbers. The regression analysis, which accounts for the underlying distribution of the sales count through a 7^{th} order polynomial, estimates that 100 000kr-, 500 000kr-, and million kroner-focal points all attract extra mass of sales, as compared to other 50 000kr price points in the distribution. All the results are significant at the 1% level. The million kroner focal point has the strongest effect on the sales count, and is estimated to attract 44% more sales than other 50 000kr price points. The data indicate that the relative strengths of the different focal points seem to be stable across the years of 2006 to 2013. Furthermore, the pull of mass at the million kroner focal point comes from both above and below in the price distribution, however the pull of mass is always greater from above than from below. This is interpreted as a pull of mass from the seller´s side of the distribution, which is a conundrum in a booming market.

The reason as to why all the prices in the sample tend to cluster, either at round numbers or at charm prices, is still not clear. And why do the round number asking prices obtain a premium in the market, when they are compared to charm asking prices? One behavioral interpretation of the results could be that the search behavior of buyers is focused on market segments. If a buyer searches for an apartment in the price range of 1 850 000 to 2 million, and another buyer searches for a dwelling in the range of 2 million to 2.3 million, then only the round number asking price of 2 million will appear in both searches. In this way, the round number asking prices might attract more buyers, perhaps due to the salience of that number.

However, the level of detail in the data does not allow for testing of those kinds of hypotheses. In the end, both rational interpretations, and behavioral interpretations of these findings are likely to contribute to further knowledge of how the housing markets truly function. It is my conjecture that our discipline will benefit from such a pluralistic approach.

Nota bene;

Change is the only constant in economics. (Curtin, 2007, p. 34)

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Appendix A

Additional Behavioral Biases with Implications for the Housing Market

Money Illusion

It has commonly been noted in the literature that loss aversion occurs in nominal terms. That is to say, people assess values in nominal terms, the reference point is often a nominal term, and the loss aversion is therefore not in relation to real prices. In relation to housing markets,Genesove and Mayer (2001) test for both nominal and real loss aversion, and find significance only for nominal loss aversion. Engelhardt (2003) concurs with this view, testing for both versions of loss aversion in his data set spanning 149 metropolitan areas of the U.S., concluding that only nominal loss aversion is significant. This is an interesting finding, and can be seen as the conjunction of two behavioral biases, namely money illusion and loss aversion. With this in mind, a brief overview of money illusion is warranted to understand how these two biases interact.

At least since Fisher (1929) published "*The Money Illusion*" the economic literature has been awash with research on the fallacy people often commit when assessing values, especially when long term comparisons are undertaken. Shafir, Diamond, and Tversky (1997) attribute money illusion to cognitive processes and the salience of nominal values. *"People attend to nominal value because it is salient, easy to gauge, and in many cases provides a reasonable estimate of real worth."(Shafir et al., 1997).* The authors demonstrate how money illusion is found in a variety of populations and in different contexts, such as contracts, law and trading. One of the survey experiments presented in the paper ask respondents to rank three hypothetical cases of selling a house. One case with nominal loss in which prices has declined 25%, but the selling price is only 23% lower, yielding a 2% profit in real terms. The second in which there is no inflation, and the selling price is 1% lower than initial purchase price, yielding 1% real loss. The third case is a nominal gain with 25% inflation and a selling price 23% higher than purchase price, yielding 2% real loss. It turns out that 48% of respondents thought the last option with a real loss of 2% was the <u>best</u> choice. 53% ranked the real gain of 2% as the <u>worst</u> option. Respondents systematically identified the non-inflationary case as the second-best outcome, but chose nominal over real gains when deciding their first-best option.

"*Loss aversion occurs relative to a reference point, and the reference point can often be nominal, yielding further manifestation of money illusion."(Shafir et al., 1997).*

In regard to loss aversion, Stephens and Tyran (2012) show in their experiment that money illusion interacts with loss aversion and constitutes nominal loss aversion for subjects' evaluation of house prices. Their incredibly rich dataset also allows them to evaluate personal traits that are correlated with nominal loss aversion. It turns out that cognitive reflection tests carry more explanatory weight than standard intelligence tests and education levels. It is suggested that the ability engage in re-thinking of first intuitions is what matters the most if nominal loss aversion is to be avoided. Ackert, Church, and Jayaraman (2011) pursue a similar survey experiment approach and finds significance of money illusion when considering house-prices. The two surveys complement each other. Interestingly Ackert, Church and Jayaraman find that although respondents suffer from money illusion, their price expectations are for future house prices are not too far from actual observed price change. The average estimate is conservative in the short run (1 year) and possibly overestimates the price growth in the medium run (5 years), which is similar to the findings of K. E. Case et al. (2012). Interestingly, they find no link between money illusion and loss aversion, which contradicts the findings of many others. This might be stemming from the nature of their dataset, which is less extensive and it is thus harder to elicit such detailed correlations.

The Disposition Effect

In behavioral finance, loss aversion is commonly referred to as one component of the disposition effect. The disposition effect is in essence the sum of investors' reluctance to realize losses <u>and</u> their inclination to sell winners. Shefrin and Statman (1985) documented the effect nearly 30 years ago, and Odean (1998) found evidence for the disposition effect in real-world stock transactions. A more recent paper tests the disposition effect in a formal theoretical framework with simulations, and discovers that prospect theory is a good explanation when preferences are defined over realized gains and losses (N. Barberis & Xiong, 2009). However, when investor preferences are defined over annual gains and losses, the model often predicts the opposite of the endowment effect; sell loosers and hold on to winners. The difference in time perspective, and more crucially, the timing of when the agent receives utility is therefore essential for the model they construct. The authors argue that the annual gain/loss-model is closer to standard models found in finance, but the realized gains/losses-model is a more compatible interpretation of prospect theory. The latter model specification allows for a distinction between paper losses and realized losses, which seem to have a substantial effect since this specification more readily produce results that are coherent with prospect theory. Mental accounting might be an explanation for the difference of the two specifications results, as investors narrowly frame investments, and only experience gain/losses when those mental accounts are closed through sales.

The predictions of prospect theory and those pertaining to the disposition effect in particular are somewhat easier to test in the context of pure financial markets. Firstly, they are traded publicly with stringent requirements to information and disclosure which generates a lot of data. The availability of broad datasets make it easier to test for the disposition effect, relative to other less transparent markets. It is valuable to focus on the part of the disposition effect that arises from the part of selling winners to early, as this is perhaps what distinguishes the disposition effect from loss aversion and the endowment effect. More on the endowment effect in the section below.

As Barberis & Xiong (2009) note, and Grinblatt and Han (2005) also argue; the common procedure in the literature is to assume prospect theory in conjuction with mental accounting as the explanation of the disposition effect.

The Endowment effect

In Novemsky and Kahneman (2005, p. 119) the disposition effect is implicitly defined as loss aversion occurring in a riskless context. The common setup for empirical enquiry is an experimental setting where half of the participants get a coffee-mug, chocolate bar or similar item of low value. The other half of the subject population get money to trade with. Participants can then freely trade (or refuse to do so) between them. Economic theory predicts that the randomized allocation of coffe-mugs and money should lead to about 50% of the mugs being traded on average. However the reoccurring finding across studies is that those who get an endowment (coffe-mug/chocolate bar) tend to require, on average, a much higher price to part with their endowment than what prospective buyers are willing to pay. This gap in the willingness-to-pay (WTP) compared to the willingness-to-accept (WTA) is what has been labeled; the endowment effect. Novemsky and Kahneman (2005) entertains the possibility that loss aversion can be seen both as a description and explanation of the endowment effect.

Richard Thaler (1980) was the first to offer prospect theory, and loss aversion in particular, as an explanation for the endowment effect (a term he coined). The endowment effect can be viewed as another incarnation of loss aversion. Agents need to exhibit loss aversion behavior in order for the endowment effect to materialize. The key point seems to be that you are given an object or even a prospect of such, and by the power vested in the act of receiving and owning something, you put a premium on that object. This leads to the endowment effect in which subjects are unwilling to part with their endowment, unless the price premium is granted. As numerous studies show, this leads to a consistent and significant discrepancy in the willingness-to-pay for an item and the willingness-to-accept for the same item. See Novemsky and Kahneman (2005) for an overview. It is this asymmetry, which constitutes the endowment effect. Given that agents do not exhibit loss-averse behavior, the endowment effect would then fail to materialize. As such, loss aversion can possibly be interpreted as a necessary condition for the endowment effect.

Chapman (1998) provide some insights into the effect the similarity of traded items has on the endowment effect. Some evidence indicates that loss aversion is declining in the similarity of traded objects. The explanation offered for this is that similar object will be interpreted as less of a loss than very dissimilar ones. This is in accordance with prospect theory's predictions. This insight can be applied to the real-estate market. In the case of the housing market, most sellers are also buyers. Shortly before or after they sell their house they will tend to buy a new one, given that the need for housing services has not changed (death, transfer to rental market etc.). Taking the findings of Chapman and applying them to the housing market can thus possibly explain the magnitude of loss aversion. If sellers perceive the market as very heterogeneous, then loss aversion is expected to be strong. If the market is perceived as very homogenous then loss aversion is expected to be weak. This highlights the findings of Karl E. Case and Shiller (1988) that people tend to think of their home as having some intrinsic worth because their dwelling is seen as something special.

This claim can be further supported by the evidence that ownership history affects the evaluation of objects (Strahilevitz & Loewenstein, 1998). It is demonstrated that the ownership period of an object, in our case a house, increases the valuation of the said object. As holding periods for homes can potentially be rather long, we can be expected to believe that this contributes to and propagates the findings of loss aversion in the market for homes.

Nash and Rosenthal (2014) elaborates on the findings by Strahilevitz and Loewenstein and finds that indeed the duration of ownership is an explanatory factor for the magnitude of the observed endowment effect. In a lottery over college housing the results yields substantial findings of the endowment effect, and it increases over time as participants actually live in their allotted rooms. Conducted through a real allocation of college dorm rooms at Stonehill College in Massachusetts, the experimenters asked the WTA for giving up their first-choice residence hall from those that had already been granted their first choice through the lottery. WTP for their first-choice option was asked of those who did not get their first-choice granted through the lottery. The results were a significantly larger threshold for the WTA compared to the WTP. Together, this supports the hypothesis of an endowment effect in relation to housing.

A follow up was conducted when the participants had been living in their residence halls for 2 months. The results were that the WTA had increased, meaning a higher compensation was required to forfeit their first-choice residence hall. The WTP was not statistically different from the initial treatment. The authors argue that this exemplifies the fact that loss aversion and the endowment effect still matters for real outcomes, and when the stakes are high (compared to chocolate bars and mugs). It also shows an increasing tendency of a stronger endowment effect over time as participants experienced life in their respective residence halls. However, the survey design of the study cannot be expected to fully mitigate the considerations of social aspects; such as living with friends, even though it was set up to eliminate influences like these.

Herding Behavior

"Herding in financial markets generates speculative bubbles when traders are tracking the decision of others, not the fundamental value of assets" (Baddeley, 2013, p. 214)

While the quote above is targeting financial markets explicitly, there is mounting evidence that this kind of behavior also occurs in housing markets (Baddeley, 2005; Hott, 2012; Lan & Lan, 2014). It should also be noted that the housing market constitutes a major part of households financial wealth, and therefore can be thought of as inherently capturing aspects of a financial market. Buying a house is one of the most critical financial decisions over the lifecycle of a household, and given the general level of financial savviness of the population, it can be a difficult decision to make.

There are different types of herding behavior emphasized in the literature. There can be herding behavior based on assumptions of rationality. That is, agents extract valuable information through the observation of others and incorporates this information into their own decision (Hung & Plott, 2001). This is called Bayesian herding and the effect of this behavior is considered an information cascade, in which useful information ripples through to the decision-maker. Hung and Plott (2001) also show that the institutional setting in which decisions are made, greatly affects the herding behavior of individuals.

The contrarian view differ in the way it underlines the non-rational cause of herding to be social influences and "group thinking". The representativeness heuristic, in which people calculate probabilities based on the ease with which different scenarios come to mind, may be a proponent of herd behavior. It also seems to be intimately linked with the theories of market sentiment, in which speculative bubbles arise because beliefs about other's beliefs are that the asset will continue to appreciate. Baddeley (2013, p. 214) argues that social learning theories and herding behavior can be traced back to John Maynard Keynes, and stresses the argument that rational herding on the individual level aggregates to irrational "speculative frenzies" on the macroeconomic level. This can be explained by a herding externality, which leads to inefficient outcomes in the aggregate (Banerjee, 1992)

Hott (2012) show that a model of herding behavior can explain a significant amount of the excess volatility in housing prices across 10 OECD countries, see Figure A.1 for an illustration of his results . Using a rational model of user costs of housing, and what he calls “the market view” (GDP, population growth, mortgage rates and construction activities are determinants of house prices) as a benchmark, he shows that house prices are excessively volatile across all the 10 countries in his sample. The volatility is of a magnitude which the fundamentals cannot adequately explain. Furthermore, Hott show that a heuristic decision rule where households deviate from the user cost of housing rational decision-making, and focus instead on *current* income and *current* supply of housing can explain more than the pure rational model of actual observed housing prices. In the end, Hott finds that a herding model where agents follow market sentiment, bidding up prices when recent market trends are better than expected, and vice versa when the opposite is true, is the best fit to actual observed housing prices. He finds that herding behavior is evident in all of the 10 countries, and that the herding model improves the MSE of the regressions by 20% on average.

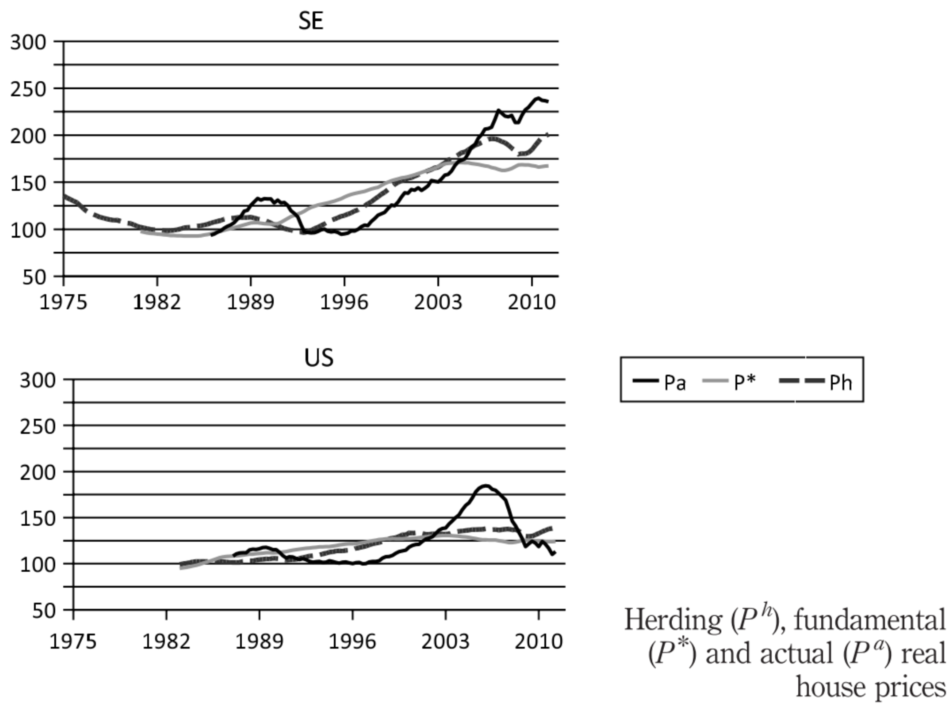

Figure A.1 – House Prices (Herding, Fundamental and Actual) in Sweden and the United States, (Hott, 2012, p. 193)

Even though research such as the one outlined above explains more of the excess volatility in housing prices than the user cost of housing model, there is still a lot of variation in prices left unaccounted for. Hott proposes that banks’ lending behavior could be one missing variable in this case. Herding behavior can also possibly affects banks at a systemic level, as discussed in Acharya and Yorulmazer (2008), and might further explain the excess volatility in the housing markets. However, at this point the literature is not conclusive at the time of writing.

Markets, Experience and Mitigation of Behavioral Biases

A common conjecture within the traditional literature is that biases are attenuated, or even fully mitigated by experience. In the world of finance, which is mostly dominated by professionals with years of experience, it has been documented that there is a propensity to sell winning stocks too early and hold on to losing stocks too long (Odean, 1998), as noted in the Disposition Effect section above. Crane and Hartzel (2010) also find that professionals managing real estate funds suffer from the disposition effect, and that this cannot be explained by any alternative explanations such as tax incentives, mean-reversion or asymmetric-information.

When it comes to loss aversion, Genesove and Mayer (2001) find that experience only attenuates approximately half of the loss aversion effect, while Bokhari and Geltner (2011) only evaluate professionals and actually find that more experienced property investors, as measured by number of trades, exhibit a *higher* degree of loss aversion. A cautious interpretation would be that experience and "professionalism" do not eliminate the effects of behavioral biases completely.

Another example comes from Kvaløy (2015), who has run through the numbers for the 2007-2013 yearly forecast-award (Samfunnsøkonomenes "Prognoseprisen") conducted by the economics labor association in Norway. He wanted to investigate if "luck" is being recognized as "skill", as Daniel Kahneman (2011a) has argued occurs frequently, and usually in industries which are human capital intensive. The premise here is that if the forecasters had measurable skills in the discipline of forecasting, then one would expect to find correlation of the performance on a year-to-year basis. In the data Kvaløy analyzed, he finds an average correlation of 0,09 for the 10 forcasting companies which are represented. This could suggest that "skill" is attributed to "luck" when it comes to forcasting.

Kahnemans original analysis was done on stock-market returns data, in which he investigated the correlation across time for stock-market funds and managers, and he found a correlation barely different from zero. The conclusion Kahneman drew was that picking an actively managed investment fund based on past performance was, on average, not significantly different from rolling a dice and letting the throw decide which fund to choose. Kvaløy did the same testing for

Norwegian investment funds over the years 2009 to 2014 and found, again, that correlation was 0,01 ~ virtually like throwing a dice!

These might be cases of over-optimism, or other deviations from rationality, but nevertheless they are congruent across time and space, and are therefore likely to be robust in many areas of decision-making. Professional forecasters do put in a lot of effort, and to the best of their ability produce forecasts that are grounded in well-established theory. The conclusion we perhaps can draw is not that the forecasters do not know what they are doing, but rather that forecasting economic variables over longer time spans is an incredibly difficult task!

The failure amongst experts to recognize the finding that, despite all their efforts, their predictions are no better than the throw of a dice, is perhaps what is most puzzling?

Appendix B

A Current Estimate of the User Cost of Housing in Norway

I adopt the notation from Himmelberg et al. (2005)

1) $Annual\ Cost\ of\ Ownership = P_t r_t^{rf} + P_t\omega_t - P_t\tau_t(r_t^m + \omega_t) + P_t\delta_t - P_t g_{t+1} + P_t\gamma_t$

Price of housing: P_t	Risk-free interest rate: r_t^{rf}	Property tax rate: ω_t	Income tax rate: τ_t
Mortgage interest rate: r_t^m	Maintenance costs: δ_t	Risk premium of owning: γ_t	Expected capital gain: g_{t+1}

It is assumed that: $Annual\ Cost\ of\ Ownership = Rental\ Cost$ because of the asset-market approach where rental market is treated as a perfect substitute for owner-occupiers. It thus follows;

2) $$R_t = P_t u_t$$

Where u_t is the right hand side of equation 1, with P_t factored out, and R_t the annual rental cost.

Thus the common relationship between price of owning and price of renting is:

3) $$\frac{P_t}{R_t} = \frac{1}{u_t}$$

Thus if we follow Himmelberg, Mayer, and Sinai's (2005) approach and adjust their numbers to the current Norwegian market;

- We can use the current Norges Bank key policy rate, unchanged as from 12.12.2014 as risk-free rate: 1,25%
- The property tax rate is by and large 0% for most households
- Income tax rate in the range of 40%
- Mortgage interest rate 3% (Statistics Norway, 2015c)
- Maintenance cost 2,5% (as in (Himmelberg et al., 2005))
- Risk premium: currently the market is pricing the risk, measured as the difference of the mortgage interest rate from the risk-free rate = 1,75% , a more conservative approach can be 2% as in (Himmelberg et al., 2005)

- Capital gains: 7.2% which was national average past year or 18% which was national average over past 10 years, both calculated with the house price index (Statistics Norway, 2015a)).

  Or 39,39% national average (1970-2003) from (Eitrheim & Erlandsen, 2004, p. 365).

We get a user cost which equates to:

$$0{,}0125 - (0{,}4 * 0{,}03) + 0{,}025 - 0{,}072 + 0{,}02 \; = \; -0{,}0265$$

This is the most conservative specification. If the longer series of national averages is employed as measure of expected capital gains, the cost goes deeper into negative territory. As noted in section 1.4.1 Himmelberg et al. (2005) suggest that the user cost is undefined when it crosses the zero lower bound. An alternative interpretation can be that the risk premium in the Norwegian market at this point in time must be extremely large, in order for the user cost equation to balance.

Appendix C

The Quality of Data & Size of The Sample

Eiendomsverdi AS, is a subsidiary of four of the largest banking constellations in Norway, and those banking constellations also have a large market involvement through subsidiary real estate agencies (DNB Eiendom, Privatmegleren (Nordea) and Eiendomsmegler 1 (Sparebank1)). Therefore, the database is constructed partly by the input of real estate agents. Eiendomsverdi AS also collaborates with FINN Eiendom AS (the largest internet marketplace for real estate in Norway) and Real Estate Norway (the national association for Norwegian realtor brokerages), ensuring that the dataset covers all real estate agencies active in Oslo.

The close collaboration with real estate agents (more than 90% of agents participate according to Eiendomsverdi AS), entails that the database is swiftly updated the day after a sale is made, and later matched against official records and registry data to ensure the quality of the record. However, as some data is typed by hand, the data may have some erroneous entries. Furthermore, the collaboration with FINN Eiendom (which is the largest online listing service by any measure) indicates that the total database of Eiendomsverdi comprise almost 92% of all residential transactions in Norway (RealEstateNorway, 2015).

The data for my analysis come from the same source as Statistics Norway use to construct their housing price index, so the quality of the data should be adequate for this study. However as Statistics Norway also note: *"The sample covers about 60 per cent of all dwelling-sales on the open market. Systematic skewness is still possible in the sample, regarding housing standard and location."* (Statistics Norway, 2015a).

The dataset I have acquired is thus a subset of that sample, and to pinpoint exactly how large the share of the transactions included in the sample is out of the total in Oslo is a difficult task. All I can offer is a qualified guess.

Real Estate Norway claims that their data covers 92% of all housing transactions in Norway, Statistics Norway says about 60%. As my dataset is a subsample of theirs, a conservative estimate would then be somewhere in the middle of those two stated ranges, with perhaps a greater weight put on Statistics Norway's estimate (They are, after all, the official statistical entity in Norway, which should give them an advantage in matters like these).

The Norwegian Housing Market

In Figure C.1, we see the Norwegian house price index from 1995 to 2012, in comparison with a selection of other OECD-countries.

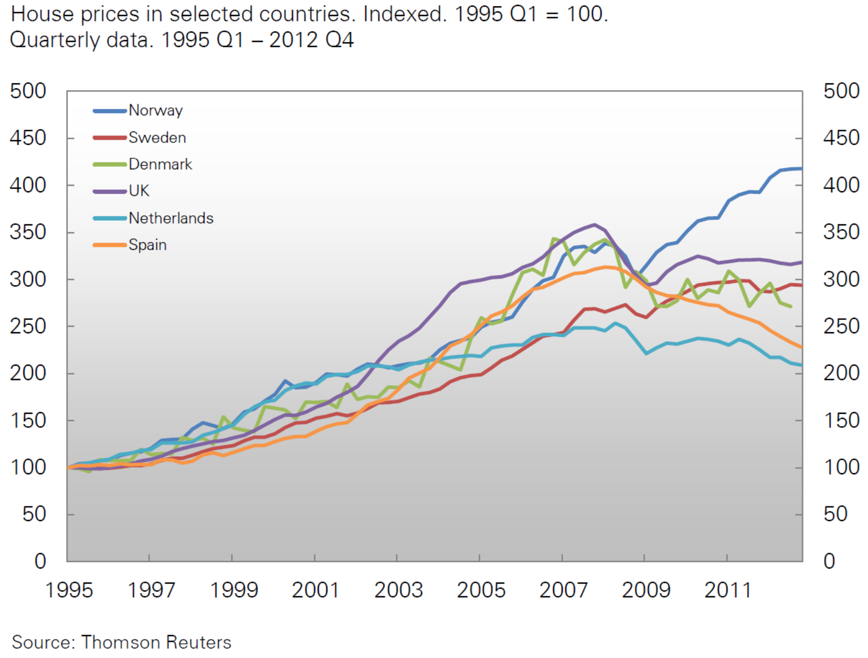

Figure C.1 - (Norges Bank, 2013) - Housing Prices in Selected Countries, Indexed. Q1 1995 = 100. Quarterly, Q1 1995- Q4 2012. Data Source: Thomson Reuters

In general, we see an upwards sloping trend with a clear downturn around the years of the financial crisis. Remarkably, Norwegian house prices quickly recovered and reverted to the previous pattern of rapid growth. Surrounding countries followed a more sideways development post-2008, with prices levelling off. In Spain and Netherlands prices continued to decline notably.

Geographical Summary Statistics

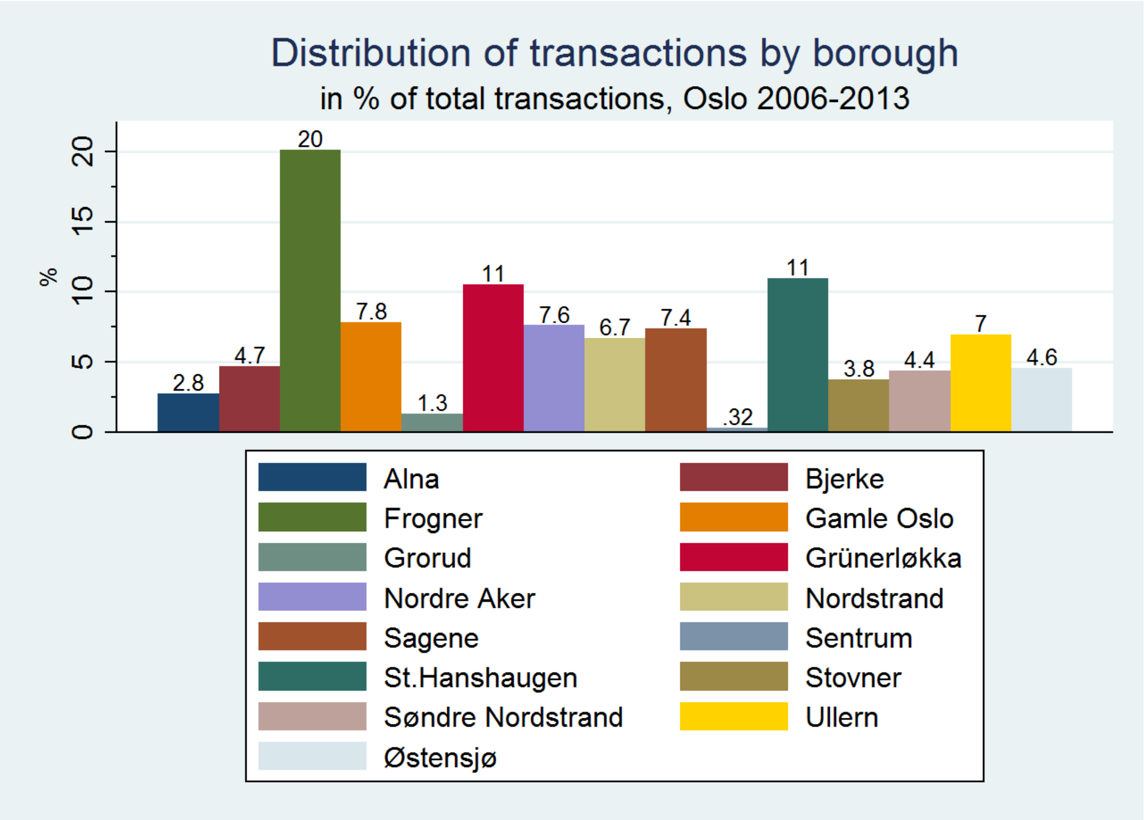

Figure C.2 – Distribution of Transactions by Borough

An overview of the geographical or spatial variance in the dataset is displayed in Figure C.2. We see that the central boroughs of Frogner, Grünerløkka, St. Hanshaugen and Sagene are responsible for almost 50% of all the transactions observed in the data. In Statistics Norway's database over dwellings in Oslo we find that those four boroughs contain 36% of all dwellings in Oslo. Thus, we can infer that those four boroughs is overrepresented in the datasample, as dwellings in the central area of Oslo tend to transact more often than others. The oversampling, as compared to when each dwelling can transact only once, is 38%.

More interestingly we see systematic differences in price levels for the different boroughs, reflecting both the variation in sizes and types of dwellings located in the boroughs.

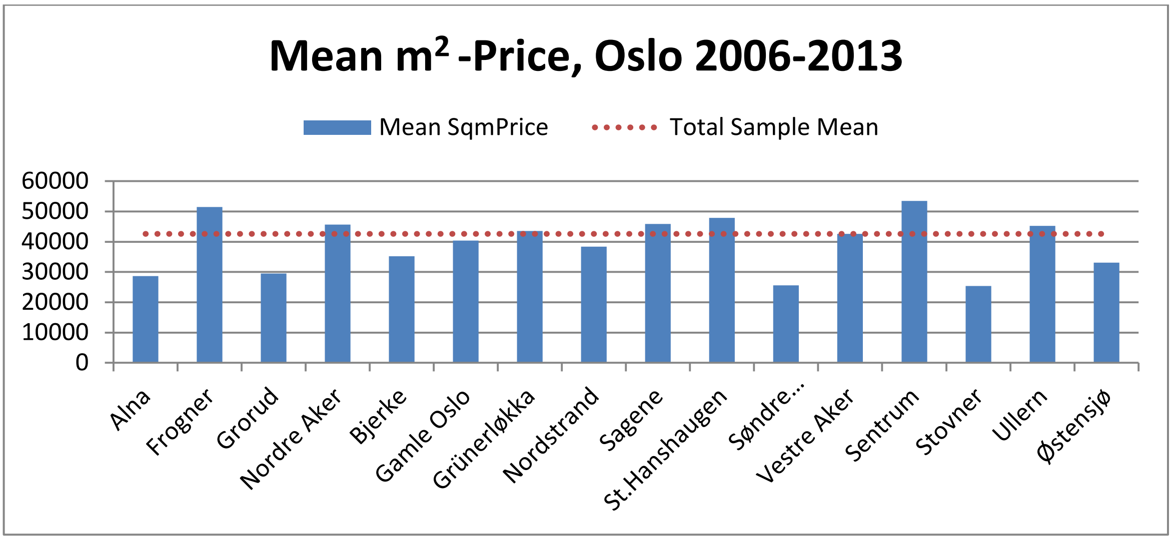

Figure C.3 – m2-Price by Borough, Oslo 2006-2014 mean.

Additionally, in Figure C.3, it may be reasonable to interpret some of the difference in price as an expression of the perceived level of housing service quality provided by the different boroughs (be it proximity to public transport, nearby attractions such as shops, cafés, or schools and recreational spaces). We see that the total sample mean is quite high due to the fact that it is the high priced central boroughs that contain the most transactions.

Variable Descriptions and Summary Statistics

The dataset is comprised of 65 969 housing transactions the last 9 years in the Oslo municipality area. There are 31 variables included in the raw dataset, ranging from geographical indicators, property characteristics, dwelling characteristics, time variables and price characteristics of the transactions. However some variables have a lot of missing entries ("Rent" is entirely missing, "RenovatedYear", "Rooms", "Floor", and "LoanValuation" all have missing values affecting the range from 20% to 95% of the observations. The core variables in the dataset, defined as variables without any missing values, are: "RegDate", "Salesprice", "Price", "SqmPrice", "LivingArea", "EstateType", "Ownership", "SiteType". In addition, geographical indicators that tie the observations to Oslo municipality are included for every observation. Variables where less than 5% of observations are missing; "AskingPrice", "Bedrooms", "Postcode", "CityDistrict" and "BuildYear". Salesprice and Price are the same, thus Price is dropped.

Variable Lists

Table C.1: Price Variables

Name of variable		Note	Observed mean in the data N=51858 SD in parenthesis
Salesprice	"Salgspris"	Is the specified amount transferred from buyer to seller.	3.546.295 (2.131.987)
Asking Price	"Prisantydning"	Is the asking price posted by sellers	3.433.484 (2.146.418)
Valuevaluation	"Verditakst"	Is the assessed market value conducted by a professional valuer/surveyor*.	3.505.722 (2.197.129)
loanvaluation	"Låneverdi"	Is a conservative estimate of market value, made by real estate agent or professional surveyor, which is thought to give the creditor sufficiently security for the mortgage given*. Is often assumed to be 80-90% of the valuevaluation. In the data the mean loan valuation is 85% of the value valuation.	3.149.864 (1.997.212) N=34031
Sqmprice = Price per square meter of living area		The ratio of: $\frac{Salesprice}{Living\ area}$	42.558 (12.572)

As defined by Norwegian Valuers and Surveyors Association;* ***Tilstandsrapport – en veiledning om begreper, ord og uttrykk* *(www.ntf.no/new/download/brosjyrer/tilstandbrosjyre.doc)*

Table C.2: Physical Attributes of Dwelling

Name of variable		Observed mean in the data N=51858
Livingarea	= "Primære rom (P-rom*)"	88,78m^2 (53,11)
Utilityfloorspace	= "Bruksareal (BRA*)"	93,29 m^2 (61,15) N=46172
Grossarea	= "Brutto areal (BTA*)"	103,84 m^2 (68,12) N=48711
Floor	The floor on which the dwelling is located	2,84 (8,15) N=41628
rooms	Number of rooms in the dwelling	2,67 (1,22) N=2630
bedrooms	Number of bedrooms in the dwelling	2,15 (1,11) N=49663
renovatedyear	Year of renovation	2004,16 (7,16) N=6381
buildyear,	Year of construction	1955,61 (39,64)
sitearea	Total area of the property-lot for the entire estate/entire building for multi-dwelling complexes	4758,95 (18148,37) N=48372
estatetype	Type of dwelling: Apartment, Detached house, Semi-Detached house or Row-house (see separate table of summary)	
ownership	Ownership status of dwelling. The data only contains self-owned properties (Selveier), *not* stock-option apartments or co-operative apartments (borettslag).	
sitetype	Leased or owned type of estate	

** As defined by Norwegian Valuers and Surveyors Association;* ***Area, measurement and definitions*** *(http://www.ntf.no/page1323637.aspx)*

Table C.3: Time Variables

Regdate	Time of registry in the market
Actualsaledate	Actual date of transaction
Publicregistrationdate	Date of public registry, when the transaction is processed by official government agency. Usually some months after actual sale date.

Table C.4: Geographical Indicators

code00	Postal code
Name	Oslo
Citydistrict	Specifying the city borough in which the dwelling resides.
Councilnumber	301
Councilname	Oslo
Countynumber	3
Countyname	Oslo

City Boroughs	Note
Alna	
Bjerke	
Frogner	
Gamle Oslo	
Grorud	
Grünerløkka	
Marka	To be excluded due to mostly containing recreational dwellings and not primary dwellings
Nordre Aker	
Nordstrand	
Sagene	
Sentrum	
St.Hanshaugen	
Stovner	
Søndre Nordstrand	
Ullern	
Vestre Aker	
Østensjø	

Appendix D

Estimation of a 7th Degree Fractional Polynomial to Control for the Underlying Distribution of Sales

Statacommand:

- **fp <salesprice>, dimension(7) replace: regress COUNT2 <salesprice>**
- **estat ic**

Fractional polynomial comparisons:

salesprice	df	Deviance	Res. s.d.	Dev. dif.	P(*)	Powers
omitted	0	677812.63	171.041	12196.55	0.000	
linear	1	673256.75	163.664	7640.68	0.000	1
m = 1	2	673256.75	163.664	7640.68	0.000	1
m = 2	4	667188.82	154.329	1572.74	0.000	-1 -.5
m = 3	6	666366.07	153.107	749.99	0.000	0 0 .5
m = 4	8	665783.86	152.248	167.78	0.000	-1 -1 -.5 -.5
m = 5	8	665684.24	152.103	68.16	0.000	-.5 0 0 0 0
m = 6	11	665646.57	152.049	30.49	0.000	-.5 0 .5 1 1 1
m = 7	13	665616.08	152.005	0.00	--	-1 -.5 -.5 0 0 .5 1

(*) P = sig. level of model with m = 7 based on F with 51642 denominator dof.

Source	SS	df	MS
Model	317808956	7	45401279.4
Residual	1.1934e+09	51648	23105.5904
Total	1.5112e+09	51655	29254.9896

Number of obs	= 51656
F(7, 51648)	= 1964.95
Prob > F	= 0.0000
R-squared	= 0.2103
Adj R-squared	= 0.2102
Root MSE	= 152.01

COUNT2	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
salesprice_1	-2.63e+11	3.60e+10	-7.31	0.000	-3.34e+11	-1.93e+11
salesprice_2	1.17e+10	1.47e+09	7.97	0.000	8.84e+09	1.46e+10
salesprice_3	-1.26e+09	1.56e+08	-8.08	0.000	-1.57e+09	-9.56e+08
salesprice_4	-8629094	1035845	-8.33	0.000	-1.07e+07	-6598828
salesprice_5	250800.4	30116.6	8.33	0.000	191771.5	309829.2
salesprice_6	-316.6025	39.21792	-8.07	0.000	-393.47	-239.735
salesprice_7	.0056684	.0007566	7.49	0.000	.0041854	.0071515
_cons	7.76e+07	9322054	8.33	0.000	5.93e+07	9.59e+07

Akaike's information criterion and Bayesian information criterion

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	51656	-338906.3	-332808	7	665630.1	665692